



AFRICA CENTER OF EXCELLENCE FOR WATER MANAGEMENT
ADDIS ABABA UNIVERSITY



**Evaluation of the Impacts of Land Use/Land Cover and Climate Change on Flood
Occurrence in the Gumara Watershed, Upper Blue Nile Basin, Ethiopia**

By
Haile Belay Desta

A Ph.D. dissertation submitted to the Africa Center of Excellence for Water Management,
Addis Ababa University, in partial fulfillment of the requirements for the Degree of Doctor of
Philosophy in Water Management (Hydrology and Water Resource Management)

**Africa Center of Excellence for Water Management
Addis Ababa University
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August, 2025

Addis Ababa, Ethiopia

Declaration

I, **Haile Belay Desta (GSR/3057/13)**, hereby declare that this research dissertation entitled **“Evaluation of the Impacts of Land Use/Land Cover and Climate Change on Flood Occurrence in the Gumara Watershed, Upper Blue Nile Basin, Ethiopia”** has been developed by me, original work and has not been submitted to any other institution for the award of any academic qualification. The content of the dissertation has not been plagiarized and where works of other researchers have been used, they have been appropriately cited.

The following parts of this dissertation work have been published in a peer review journal:

- 1) Evaluation and comparison of the performances of the CMIP5 and CMIP6 models in reproducing extreme rainfall in the Upper Blue Nile basin of Ethiopia
- 2) Scenario-Based Land Use and Land Cover Change Detection and Prediction Using the Cellular Automata–Markov Model in the Gumara Watershed, Upper Blue Nile Basin, Ethiopia
- 3) Identifying Flood Source Areas and Analyzing High-Flow Extremes Under Changing Land Use, Land Cover, and Climate in the Gumara Watershed, Upper Blue Nile Basin, Ethiopia
- 4) Flood Inundation Mapping Using the Google Earth Engine and HEC-RAS Under Land Use/Land Cover and Climate Changes in the Gumara Watershed, Upper Blue Nile Basin, Ethiopia

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06 August 2025



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Approved by the Board of Examiners

This is to certify that we have read this Ph.D. research proposal and that in our opinion; it is fully adequate, in scope and quality, as a Ph.D. dissertation for the Degree of Doctor of Philosophy in Water Management (Hydrology and Water Resource Management).

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Dedication

This PhD work is dedicated to my beloved son, Yabtsega Haile, whose love and joy have been a source of strength throughout this journey.

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ACEWM, AAU, 2025

LIST OF ARTICLES

Belay, H., Melesse, A.M. & Tegegne, G. Evaluation and comparison of the performances of the CMIP5 and CMIP6 models in reproducing extreme rainfall in the Upper Blue Nile basin of Ethiopia. *Theor Appl Climatol* 155, 9471–9496 (2024). <https://doi.org/10.1007/s00704-024-05187-z>

This study evaluates and compares the performance of CMIP5 and CMIP6 climate models in simulating extreme rainfall events in the Upper Blue Nile (UBN) basin of Ethiopia. It assesses model accuracy in reproducing observed extremes and analyzes the spatial and temporal variability and trends of extreme rainfall indicators within the basin.

Belay, H., Melesse, A. M., & Tegegne, G. (2024). Scenario-Based Land Use and Land Cover Change Detection and Prediction Using the Cellular Automata–Markov Model in the Gumara Watershed, Upper Blue Nile Basin, Ethiopia. *Land*, 13(3), 396. <https://doi.org/10.3390/land13030396>

This paper investigates land use and land cover (LULC) changes in the Gumara watershed, located in the UBN basin of Ethiopia. It also predicts future LULC patterns under different scenarios using the Cellular Automata–Markov (CA–Markov) model.

Belay, H., Melesse, A. M., Tegegne, G., & Tamiru, H. (2025). Identifying Flood Source Areas and Analyzing High-Flow Extremes Under Changing Land Use, Land Cover, and Climate in the Gumara Watershed, Upper Blue Nile Basin, Ethiopia. *Climate*, 13(1), 7. <https://doi.org/10.3390/cli13010007>

This study investigates the impact of land use/land cover (LULC) and climate changes on high-flow extremes in the Gumara watershed, located in the UBN basin of Ethiopia. Using hydrological modeling and scenario-based analysis, the study identifies flood source areas and assesses how shifts in LULC and climate influence flood magnitude.

Belay, H.; Melesse, A.M.; Tegegne, G.; Kassaye, S.M. Flood Inundation Mapping Using the Google Earth Engine and HEC-RAS Under Land Use/Land Cover and Climate Changes in the Gumara Watershed, Upper Blue Nile Basin, Ethiopia. *Remote Sensing* 2025, 17(7), 1283. <https://doi.org/10.3390/rs17071283>

This study integrates Google Earth Engine (GEE) and HEC-RAS modeling to map flood inundation in the Gumara watershed, UBN basin, Ethiopia, under changing LULC and climate conditions. The research highlights the utility of cloud-based remote sensing and hydrodynamic modeling in assessing flood risks and evaluating the spatial extent of flooding under historical and future scenarios.

TABLE OF CONTENTS

ACKNOWLEDGMENTS.....	i
LIST OF ARTICLES	ii
TABLE OF CONTENTS	iii
LIST OF TABLES	vii
LIST OF FIGURES.....	ix
LIST OF ACRONYMS AND ABBREVIATIONS	xiii
ABSTRACT	xv
CHAPTER 1.....	1
1.1. Introduction	1
1.2. Problem Statement.....	3
1.3. Research objective.....	5
1.4. Research Question	5
1.5. Scope and Limitations of the Study.....	6
1.6. Significance of the Study.....	6
1.7. Structure of the dissertation.....	7
CHAPTER 2.....	8
2.1. Overall Methodology of the Study	8
2.2. Conceptual Framework of the Study	10
CHAPTER 3.....	11
3. Evaluation and comparison of the performances of the CMIP5 and CMIP6 models in reproducing extreme rainfall in the Upper Blue Nile basin of Ethiopia	11
3.1. Introduction	11
3.2. Materials and Methods	14
3.2.1. Study Area	14
3.2.2. Datasets.....	15
3.2.3. Overall Methodology.....	17
3.2.4. Data Quality Control	18
3.2.5. Random Forest Merging (RF-MERGE)	18
3.2.6. Performance Evaluation of Gridded Rainfall Products and Merged Rainfall Estimates.....	19
3.2.7. Extreme Rainfall Indices	20
3.3. Results	27
3.3.1. Mean Rainfall Climatology Of The UBN Basin	27
3.3.2. Performance Evaluation of Gridded Rainfall Products and Merged Estimates.....	28
3.3.3. Performance of GCMs in Reproducing Extreme Rainfall Indices and Monthly Rainfall	30
3.3.4. Ranking Of The CMIP5 And CMIP6 Models.....	32
3.3.5. Comparison of the CMIP5 and CMIP6 Models	33

3.3.6. Evaluation of Bias Correction Methods	37
3.3.7. Spatial Distribution of Extreme Rainfall Indices.....	38
3.3.8. Changes in Extreme Rainfall Indices	39
3.3.9. Trends, Variability, and Correlation of Extreme Rainfall Indices.....	40
3.4. Discussion	43
3.4.1. Observed Extreme Rainfall Indices.....	43
3.4.2. Performance Evaluation of the GCMS in Reproducing Extreme Rainfall Indices	43
3.4.3. Variability and Trends of Extreme Rainfall Indices.....	44
3.5. Conclusions	45
CHAPTER 4.....	47
4. Scenario-Based Land Use and Land Cover Change Detection and Prediction Using the Cellular Automata– Markov Model in the Gumara Watershed, Upper Blue Nile Basin, Ethiopia	47
4.1. Introduction	48
4.2. Materials and Methods	51
4.2.1. Study Area	51
4.2.2. Data Used	52
4.2.3. Overview of the Methodology.....	54
4.2.4. LULC Classification and Change Detection	55
4.2.5. LULC Prediction	59
4.3. Results	64
4.3.1. LULC Classification.....	64
4.3.2. Accuracy Assessment.....	66
4.3.3. Variable Importance	67
4.3.4. Change detection (1985–2019).....	68
4.3.5. LULC Change Driver Variables.....	71
4.3.6. Transition Probability Matrix (TPM)	72
4.3.7. Transition Suitability Maps (TSMs).....	73
4.3.8. Validation of the CA–Markov Model	74
4.3.9. LULC Prediction	75
4.3.10. Change Detection (2019–2065).....	77
4.4. Discussion	79
4.4.1. LULC Classification and Change Detection	79
4.4.2. Impacts of LULC Change on Socioeconomic and Environmental Conditions	80
4.4.3. Relevance of Scenario-Based LULC Change Detection and Prediction to Policy and Practice	82
4.5. Conclusions	82
CHAPTER 5.....	84
5. Identifying Flood Source Areas and Analyzing High-Flow Extremes under Changing Land Use/Land Cover, and Climate in the Gumara Watershed, Upper Blue Nile Basin, Ethiopia	84

5.1. Introduction	85
5.2. Materials and Methods	89
5.2.1. Study area	89
5.2.2. Data Used	90
5.2.3. Methods	93
5.2.4. Data Quality Control	95
5.2.5. Random Forest Merging (RF-MERGE)	96
5.2.6. Design Rainfall and Depth–Duration–Frequency (DDF) Curve	97
5.2.7. Bias Correction	98
5.2.8. Rainfall–Runoff Modeling	98
5.2.9. Flood Source Area Identification (FSAI)	104
5.2.10. Combined Impacts of LULC and Climate Change on High-Flows.....	105
5.3. Results	105
5.3.1. Mean Monthly and Annual Rainfall	105
5.3.2. Design rainfall and depth–duration–frequency (DDF) curve	107
5.3.3. Annual maximum (AM) 1-day rainfall.....	107
5.3.4. LULC Change Analysis.....	108
5.3.5. Hydrological Modeling	109
5.3.6. Return Period-Based Peak Discharge and Runoff Volume Simulation	113
5.3.7. Flood Source Area Identification (FSAI)	115
5.3.8. Combined impacts of LULC and climate change on high-flows	117
5.4. Discussion	120
5.4.1. FSAI and Analysis of High-Flow Extremes.....	120
5.4.2. Generalizability of the Study Findings	122
5.4.3. Limitations of the Study and Future Research Directions	122
5.5. Conclusions	123
CHAPTER 6.....	124
6. Flood Inundation Mapping Using the Google Earth Engine and HEC-RAS under Land Use/Land Cover and Climate Changes in the Gumara Watershed, Upper Blue Nile Basin, Ethiopia.....	124
6.1. Introduction	125
6.2. Materials and Methods	127
6.2.1 Study Area	127
6.2.2 Data Used	129
6.2.3 Methodological Framework of the Study	130
6.2.4 SAR-Based Flood Inundation Mapping	131
6.2.5 Hydraulic Flood Modeling	134
6.3. Results	143
6.3.1 SAR-Based Flood Inundation Mapping	143

6.3.2 Hydraulic Flood Modeling	150
6.3.3 Comparison of Flood Frequency Maps	159
6.4. Discussion	160
6.4.1 SAR-Derived Flood Inundation Mapping	160
6.4.2 HEC-RAS 2D Flood Modeling	162
6.4.3. Future Research Directions	163
6.4. Conclusions	163
CHAPTER 7	164
7.1. Synthesis of the Overall Findings of the Study	164
7.2. Implications of the Study for Integrated Flood Risk Management	166
7.3. Methodological Contributions and Applicability	167
CHAPTER 8	168
8. Summary, Conclusions, and Recommendations	168
8.1. Summary	168
8.2. Conclusions	169
8.3. Recommendations	170
References	171
Appendix	189

LIST OF TABLES

Table 3.1. GCM names, resolutions, modeling centers, and countries for the CMIP5 (indicated in bold) and CMIP6 global climate models.	17
Table 3.2. List and descriptions of selected ERFIs	21
Table 3.3. Mean monthly and annual rainfall (mm) in the UBN basin 1981–2005, estimated using observed rainfall, gridded rainfall products, and the merged estimate based on RF-MERGE.	28
Table 3.4. Average TOPSIS ranking scores of GCMs for reproducing ERFIs and monthly rainfall.	32
Table 3.5. K-S test statistics for the cumulative distribution functions (CDFs) of the model simulated (uncorrected) and bias-corrected mean monthly rainfall based on the LS, DM, QM, and CDF-t methods.	38
Table 3.6. Mann-Kendall (M-K) trend Z statistics, P-value, slope, and coefficient of variation of extreme rainfall indices (ERFIs) for the observation period from 1981 to 2019.	42
Table 3.7. Correlations (<i>R</i>) between extreme rainfall indices for the study basin during the observation period (1981–2019).	43
Table 4.1. Description of Landsat surface reflectance images used for LULC classification of the Gumara watershed.	53
Table 4.2. Description of identified LULC classes in the Gumara watershed.	53
Table 4.3. Area and percentage of each LULC class in the Gumara watershed for the four historical years (1985, 2000, 2010, and 2019).	66
Table 4.4. Results of the classification accuracy assessment in terms of the overall accuracy (OA) and kappa coefficient (K).	67
Table 4.5. Percent change (Δ) in (%) and annual rate of change (Δ) in km ² /year for the four study periods.	69
Table 4. 6. Gain and loss of each LULC class for the four study periods.	70
Table 4.7. Cramer’s V values of LULC driver variables.	71
Table 4.8. (a) Transition probability matrix of LULC classes in the Gumara watershed: (a) from 1985 to 2000, (b) from 2000 to 2010, (c) from 2010 to 2019, and (d) from 1985 to 2019.	72
Table 4.9. Predicted area and percentage of LULC classes in the Gumara watershed in 2019 and in 2035 and 2065 under the BAU and GOV scenarios.	77
Table 4.10. (a) Gains and losses of LULC classes between 2019 and 2065 under the BAU scenario. (b) Gains and losses of LULC classes between 2019 and 2065 under the GOV scenario.	78
Table 5.1. Location and elevation information of the eight ground-based meteorological stations located in and around the Gumara watershed.	91
Table 5.2. Descriptions of the NASA NEX-GDDP dataset (CMIP5 and CMIP6 climate models) used in this study.	91
Table 5.3. Characteristics of subwatersheds (area, slope, longest flow path length and slope, centroidal flow path length and slope, and drainage density).	110
Table 5.4. Changes in peak discharge due to changes in the runoff curve number (CN) with $\pm 25\%$ for selected events (from 13 August to 31 August 2010).	111
Table 5.5. Model performance evaluation during calibration and validation.	113
Table 5.6. Calibrated model parameter values for the runoff volume, direct runoff, and routing models.	113
Table 5.7. Changes in peak discharge and runoff volume for different return periods between LULC-1985 and LULC-2019.	114
Table 5.8. Comparison of 50-year peak discharge generation in the Gumara watershed under different land use conditions.	116
Table 5.9. Change in high flow of the Gumara watersheds under combined climate (RCP and SSP) and land use (BAU-2035, BAU-2065, GOV-2035, and GOV 2065) scenarios.	118
Table 5.10. The mean annual maximum flow (<i>Q</i>) of the Gumara watershed, in m ³ /s, across different probability of exceedance ranges, as estimated under combined climate and land use scenarios.	119
Table 6.1. Depth–velocity product (DVP) method for flood hazard classification (DEFRA, 2005)	142

Table 6. 2. Optimal threshold values and SAR-derived flood inundation areas from 2017–2021.....	149
Table 6.3. Sensitivity of the maximum flood depth and inundation area to changes in Manning’s roughness coefficient (n).	152
Table 6. 4: Min, max, average, and calibrated Manning’s roughness n values for different land use types of the three flood events.	153
Table 6.5. Model performance metrics before and after calibration for the two flood events of 2019.	153
Table 6. 6. Confusion matrix for the validation of the HEC-RAS flood inundation map using ground control points (GCPs) and corresponding accuracy assessment results.	156
Table 6. 7. Flood inundation extent and depth for different return periods.....	158
Table 6.8. Flood inundation extent and average flood depth and change analysis results between the historical and future periods.	159

LIST OF FIGURES

Figure 2. 1: Overall conceptual framework of the study	10
Figure 3.1. Location map of the study area. (a) Location map of Ethiopia within the Africa context; (b) river basins of Ethiopia; and (c) meteorological stations, river network, and elevation map of the Upper Blue Nile basin.	15
Figure 3.2. Statistical and categorical performance measures for daily rainfall data of the three gridded rainfall products and merged estimates at testing stations from 1981 to 2005. First row (a-c) shows heatmap statistical performance measures (<i>R</i> , <i>RMSE</i> , and <i>PBIAS</i>). Second row (d-f) shows box and whisker plots of categorical performance measures (<i>POD</i> , <i>FAR</i> , and <i>CSI</i>), where the green dashed lines show the optimal values of each categorical measure.	30
Figure 3.3. Heatmap of the statistical performance measures (<i>R</i> , <i>RMSE</i> , and <i>PBIAS</i>) for the CMIP5 (a-c) and CMIP6 (d-f) models in reproducing observed extreme rainfall indices and monthly rainfall (1981-2005).....	31
Figure 3.4. Taylor diagrams of the 8 extreme rainfall indices and monthly rainfall simulated from the 8 CMIP5 and CMIP6 models for the period from 1981 to 2005. The dots and triangles with different colours represent the CMIP5 and CMIP6 models, respectively.	35
Figure 3.5. Taylor skill scores (<i>Tss</i>) of the CMIP5 and CMIP6 climate models for the 8 ERFIs and monthly rainfall.	36
Figure 3.6. Spatial distributions of the observed and projected ERFIs. (a) Long term observed (1981–2019), (b) RCP4.5 (2031–2055), (c) RCP4.5 (2056–2080), (d) RCP8.5 (2031–2055), (e) RCP8.5 (2056–2080), (f) SSP2-4.5 (2031-2055), (g) SSP2-4.5 (2056-2080)), (h) SSP5-8.5 (2031-2055), (I) SSP5-8.5 (2056-2080).....	39
Figure 3.7. (a) to (h) Long-term temporal variation in the 8 extreme rainfall indices, (i) histogram and probability density function (pdf) of the monthly rainfall series, and (j) cumulative distribution function (CDF) of the monthly rainfall series over the UBN basin (1981–2019). The black dashed line shows the linear trend line of each extreme rainfall index.	41
Figure 4.1. Location map of the study area: (a) river basins of Ethiopia, Upper Blue Nile Basin, and Lake Tana subbasin; (b) Lake Tana subbasin, Lake Tana, and Gumara watershed; and (c) Gumara watershed boundary, location of towns, road networks, river networks, and elevation map of the Gumara watershed.	52
Figure 4.2. Methodological framework of the study: (a) LULC classification and change detection, and (b) LULC prediction.	55
Figure 4.3. Computed NDVI images of the Gumara watershed for the years (a) 1985, (b) 2000, (c) 2010, and (d) 2019.	57
Figure 4.4. Computed SAVI images of the Gumara watershed for the years (a) 1985, (b) 2000, (c) 2010, and (d) 2019.	57
Figure 4.5. Map of driver variables: (a) elevation, (b) slope, (c) distance from streams, (d) distance from roads, (e) distance from towns, and (f) evidence likelihood.	61
Figure 4.6. LULC maps of the Gumara watershed for (a) 1985, (b) 2000, (c) 2010, and (d) 2019. The values in the legend indicate the percentage of each LULC class.	65
Figure 3.7. Area of each LULC class in the Gumara watershed for the four historical years (1985, 2000, 2010, and 2019).....	66
Figure 4.8. (a) UA and (b) PA assessment results for each class for the LULC maps for the years 1985, 2000, 2010, and 2019.	67
Figure 4.9. Relative variable importance (%) for the four datasets used for mapping LULC in the Gumara watershed: (a) Landsat-5/TM (1985), (b) Landsat-5/TM (2000), (c) Landsat 5/TM (2010), and (d) Landsat-8/OLI (2019).....	68
Figure 4.10. Net change (gain-loss) in each LULC class for the four study periods (1985–2000, 2000–2010, 2010–2019, and 1985–2019).....	70

Figure 4. 11. Contribution of each LULC class to the net change in cultivated land: (a) 1985–2000, (b) 2000–2010, (c) 2010–2019, and (d) 1985–2019.	71
Figure 4.12. Potential for transition: (a) shrubland to cultivated land and (b) cultivated land to settlement. TP is the transition potential. The greater the TP is, the greater the possibility of a transition from one class to another. The gray shaded regions show the orientation gradients of the transition potential.....	74
Figure 4. 13. LULC maps (2019): (a) reference LULC map and (b) CA–Markov model-predicted LULC map under the BAU scenario.	75
Figure 4.14. Comparison of the reference (baseline) and predicted areas of the LULC classes in the Gumara watershed in 2019.....	75
Figure 4.15. Predicted LULC maps of the Gumara watershed: (a) for 2035 and (b) for 2065 under the BAU scenario; (c) for 2035 and (d) for 2065 under the GOV scenario.....	77
Figure 4.16. Net changes (gain-losses): (a) net change (2019–2065) under the BAU scenario and (b) net change (2019–2065) under the GOV scenario.....	79
Figure 5.1. Location map of the study area. (a) Location map of the Upper Blue Nile (UBN) basin within the 12 river basins of Ethiopia. (b) Location map of the upstream Gumara watershed (bounded by a red rectangle) within the Lake Tana subbasin, and (c) Detailed map showing the rainfall and streamflow gauging stations, stream network, climate model grid (25 km × 25 km), and grid center for the NASA dataset, and elevation map of the upstream (flood source area) part of the Gumara watershed.....	90
Figure 5. 2. Elevation, slope, hydrologic soil groups, and historical and projected land use and land cover maps of the Gumara watershed for the historical and future periods.	93
Figure 5. 3. Methodological framework of the study.	95
Figure 5.4. Observed ground-based rainfall and discharge data from 1981 to 2019 for the Gumara watershed. (a) Double mass curve analysis, (b) mean annual rainfall of each ground-based rainfall station, (c) mean monthly rainfall, and (d) mean monthly discharge.....	96
Figure 5.5. A 30 m spatial resolution gridded runoff curve numbers for the historical years (a–d) and future scenarios (e–h). The gray shaded areas that bound in the figure illustrate the gradient orientation of the runoff curve number, with maximum values along the north and south directions and minimum values in the middle of the watershed.....	101
Figure 5.6. Historical and projected mean monthly rainfall (mm/month) of the Gumara watershed,.....	106
Figure 5.7. Spatial distribution of mean annual rainfall (MARF) in the historical (1981–2005) and two future periods, near-future (2031–2056) and far-future (2056–2080), under different climate scenarios.	106
Figure 5. 8. (a) Temporal variation of the long-term annual maximum (AM) 1-day rainfall series from RF-MERGE estimates (1981–2019) and (b) depth–duration–frequency (DDF) curve developed from RF-MERGE rainfall. In panel (a), the red line illustrates the increasing linear trend of annual maximum 1-day rainfall. .	106
Figure 5.9. Box plot of historical (1981–2005) and projected (2031–2080) annual maximum (AM) 1-day rainfall.	108
Figure 5.10. Percentage coverage of land use and land cover (LULC) classes of the Gumara watershed. (a) Historical years (1985, 2000, 2010, and 2019) and (b) future years (2035 and 2065) under the business-as-usual (BAU) and governance (GOV) scenarios.....	109
Figure 5.11. Delineated subwatershed’s area, centroids, and stream network of the Gumara watershed as delineated in the HEC-HMS model.....	110
Figure 5.12. Model sensitivity analysis for the runoff curve number (CN) from 13 August to 31 August 2010	111
Figure 5.13. Observed and simulated discharge for selected events: (a) Event 1 (calibration), from 1 July to 31 August 1996; (b) Event 2 (calibration), from 5 July to 31 July 2008; (c) Event 3 (validation), from 2 August to 27 August 2014.	112

Figure 5.14. (a) Comparison of simulated peak discharge (Q) under various land use conditions across different return periods and (b) comparison of simulated runoff volume (V) under various land use conditions across different return periods.	114
Figure 5.15. Computed flood index (fi) values estimated using the Unit Flood Response (UFR) approach for a 50-year return period peak discharge under different LULC conditions.....	117
Figure 5.16. Comparison between historical and future annual maximum 1-day flow duration curves. (a) Future climate combined with the BAU land use scenario and (b) future climate combined with the GOV land use scenario.....	119
Figure 6.1. Location map of the study area. (a) The Upper Blue Nile (UBN) basin and the Lake Tana subbasin within the context of Ethiopia's 12 river basins, (b) the Gumara watershed in the context of the Lake Tana subbasin, and (c) detailed features of the study area, including the streamflow gauging station, flood-prone area, Gumara River (downstream section), and elevation map.....	128
Figure 6. 2. (a) Mean monthly rainfall of the Gumara watershed (1981–2019) and (b) mean monthly streamflow of the Gumara River at the Wanzaye gauging station (1981–2019).	129
Figure 6.3. Overall methodological framework of the study.....	131
Figure 6.4. Terrain modification in triangular irregular (TIN) format. (a) Original terrain model, (b) modified terrain model, and (c) details of the modified terrain model showing the Gumara River (channel) and elevation variation in the floodplain area found at the left bank of the river.	136
Figure 6.5. Boundary conditions and land use/land cover (LULC) map of the floodplain area for 2019. In the legend, the values indicated in brackets represent the ranges of Manning's n values corresponding to different LULC classes, as recommended by Chow (1959).	138
Figure 6.6. (a) Inflow hydrographs for different return periods (5, 10, 25, 50, and 100 years) and (b) inflow hydrographs for the extreme conditions of the historical (1981–2005), near-future (2031–2055), and far-future (2056–2080) periods, based on the SSP5-8.5 high-emission scenario.	143
Figure 6.7. Preprocessed and speckle-filtered Sentinel-SAR images. (a) Before flood (composite image of January 11 and 23, 2019); (b) after flood (July 22, 2019); (c) after flood (August 3, 2019); and (d) after flood (August 27, 2019).....	145
Figure 6.8. Difference images for the flood event of 2019: (a) July 22, 2019; (b) August 3, 2019); and (c) August 27, 2019.	146
Figure 6.9. Frequency distributions (histograms) of flooded and nonflooded pixels in the difference image for three flood events: (a) July 22, 2019; (b) August 3, 2019; and (c) August 27, 2019; (d) percentage of flooded pixels for different threshold values. The red dashed line represents the threshold value used to separate flooded and nonflooded areas.	147
Figure 6.10. SAR-based flood inundation maps of the study area: (a) July 22, 2019; (b) August 03, 2029; and (c) August 27, 2019.	148
Figure 6.11. SAR-based time series inundation maps (2017–2019). Panels (a–e) show the inundation extent for different time periods, whereas panel (f) presents the flood frequency map. In panel (f), the dark blue areas within the red rectangle indicate frequently flood-affected regions.	149
Figure 6.12. Sensitivity of (a) the maximum flood depth and (b) flood inundation area to changes in Manning's roughness coefficient (n) for the August 5, 2019 flood event.	151
Figure 6.13. HEC-RAS model-computed flood inundation depth maps for (a) July 22, 2019; (b) August 3, 2019; and (c) August 27, 2019.	154
Figure 6.14. (a) HEC-RAS-derived flood inundation map for August 30, 2019. (b) Sentinel-2 satellite imagery for August 30, 2019, and ground control points (GCPs). The flood area GCPs are marked in blue, whereas the nonflooded area GCPs are shown in yellow.....	155
Figure 6.15. Flood depth, velocity, and hazard maps for the flood event of August 3, 2019: (a) computed flood depth (max=7.32 m), (b) computed flood velocity (max=1.58 m/s), and (c) flood hazard map. In (c), H1, H2,	

H3, and H4 represent low, moderate, significant, and extreme hazard levels, respectively, classified on the basis of the depth–velocity product (DVP).	157
Figure 6.16. (a), (b), (c), (d), and (e) show flood inundation maps for different return periods for 5-, 10-, 25-, 50-, and 100-year return periods, respectively.	158
Figure 6. 17. (a) Flood inundation maps for the historical (1981–2005), (b) near-future (2031–2055), and (c) far-future (2055–2080) periods under the SSP5-8.5 climate scenario.....	159
Figure 6.18. Comparison of flood inundation maps for the study area based on SAR and HEC-RAS for a 5-year return period.	160

LIST OF ACRONYMS AND ABBREVIATIONS

ACRONYMS	DESCRIPTION
BAU	Business as Usual (scenario)
CA	Cellular Automata
CHIRPS	Climate Hazards Group InfraRed Precipitation with Station
CMIP5	Coupled Model Intercomparison Project Phase 5
CMIP6	Coupled Model Intercomparison Project Phase 6
DEM	Digital Elevation Model
ERA5-Land	Fifth Generation ECMWF Atmospheric Reanalysis for Land Applications
ERFIs	Extreme Rainfall Indices
ETCCDI	Expert Team on Climate Change Detection and Indices
FSAI	Flood Source Area Identification
GCMs	General Circulation Models
GEE	Google Earth Engine
GIS	Geographic Information Systems
GOV	Governance (Scenario)
GRFPs	Gridded Rainfall Products
HEC-HMS	Hydrologic Engineering Center–Hydrologic Modeling System
HEC-RAS	Hydrologic Engineering Center–River Analysis System
IDW	Inverse Distance Weighting
IPCC	Intergovernmental Panel on Climate Change
LCM	Land Change Modeler
LULC	Land Use/Land Cover
MCE	Multicriteria Evaluation
MSWEP	Multi-Source Weighted-Ensemble Precipitation
ML	Maximum Likelihood
NDVI	Normalized Difference Vegetation Index
NEX-GDDP	NASA Earth Exchange–Global Daily Downscaled Projection
NGOs	Non-Governmental Organizations
NSE	Nash–Sutcliffe efficiency
PBIAS	Percent Bias
R	Pearson Correlation Coefficient

RCP	Representative Concentration Pathway
RF-MERGE	Random Forest Merging algorithm
RMSE	Root Mean Square Error
SAR	Synthetic Aperture Radar
SRTM	Shuttle Radar Topography Mission
SSP	Shared Socioeconomic Pathway
TOPSIS	Technique for Order Preferences by Similarity to Ideal Solution
UBN	Upper Blue Nile basin
UN-OCHA	United Nations Office for the Coordination of Humanitarian Affairs

ABSTRACT

Floods are among the most destructive natural hazards worldwide, with their frequency and intensity exacerbated by changes in land use/land cover (LULC) and climate. Vegetation cover and climatic variables are also interlinked, further influencing hydrological processes. Thus, this study evaluated the impacts of LULC and climate changes on flood occurrence and explored the relationships between vegetation cover and climate variables. Extreme rainfall analysis and vegetation–climate relationships were assessed at the basin scale in the Upper Blue Nile (UBN) Basin of Ethiopia, whereas LULC change detection and flood modelling were conducted at the watershed scale in the Gumara watershed, which is located in the UBN Basin. The study comprises four interrelated specific objectives. First, the performances of eight CMIP5 and eight CMIP6 general circulation models (GCMs) in reproducing observed extreme rainfall indices (ERFIs) for the baseline period (1981–2005) were evaluated. The GCMs were assessed via statistical metrics (correlation, RMSE, and PBIAS) and ranked via the technique for order preferences by similarity to ideal solution (TOPSIS). The four best-performing models (MIROC5, MRI-CGCM3, CanESM2, and MPI-ESM-LR from CMIP5 and MPI-ESM1-2-LR, MRI-ESM2-0, CNRM-CM6-1, and BCC-CSM2-MR from CMIP6) were bias-corrected, and their ensembles were used for projecting extremes for the future period (2031–2080) under the RCP4.5, RCP8.5, SSP2-4.5, and SSP5-8.5 scenarios. Second, historical and future LULC changes were analysed in the Gumara watershed. LULC maps for 1985, 2000, 2010, and 2019 were generated via a random forest classifier on the Google Earth Engine (GEE) platform, which achieved high overall accuracies. Future LULC maps for 2035 and 2065 under business-as-usual (BAU) and governance (GOV) scenarios were projected via the Cellular Automata–Markov (CA–Markov) model. The results revealed considerable expansion of cultivated land and settlements under BAU and a relative increase in forest cover under GOV. Third, rainfall-runoff modelling was conducted in the Gumara watershed via the Hydrologic Engineering Center–Hydrologic Modelling System (HEC–HMS) for various return periods and combined LULC and climatic scenarios. CombinedThe combined impacts of LULC and climate changes on annual maximum (AM) flows were quantified, indicating an increasing trend under future scenarios. In particular, the highest flow is expected under the SSP5–8.5 (2056–2080) climate scenario combined with the BAU-2065 land use scenario. Additionally, flood source area identification (FSAI) was performed in this part of the study on the basis of the unit flood response (UFR) approach to prioritize subwatersheds contributing most to peak flows. Finally, flood inundation mapping was conducted by integrating synthetic aperture radar (SAR)-based change detection and thresholding methods on the GEE platform and HEC-RAS 2D hydrodynamic modelling. Sentinel-1 SAR images were used to map flood inundation from 2017–2021, and the HEC-RAS model was

calibrated and validated via SAR-derived flood inundation maps. Future inundation maps indicated increased flood extents, primarily attributed to LULC and climate changes. Overall, this study provides a comprehensive assessment of how coupled LULC and climate changes influence flood risk and how climatic variables affect vegetation cover. The findings offer a scientific basis for flood risk management, watershed conservation planning, and policy formulation under future climate and land development scenarios. Moreover, the methods and results presented herein provide a valuable framework for similar studies in other regions undergoing rapid environmental and climatic changes.

Keywords: Flood occurrence, land use/land cover change, climate change, CMIP5, CMIP6, extreme rainfall indices, HEC-HMS, HEC-RAS, SAR, GEE, Gumara watershed, Upper Blue Nile basin.

CHAPTER 1

1.1. Introduction

Floods are among the most frequently occurring natural disasters and have significant impacts on human life, property, socioeconomic development, and agricultural productivity (Eccles et al., 2019; Shah et al., 2017). In Ethiopia, the increasing frequency of flood events has caused serious challenges in many regions, primarily due to the country's limited adaptation capacity (Adane et al., 2022; Fekadu, 2018; Getahun & Gebre, 2015; Taye & Dyer, 2024). The United Nations Office for the Coordination of Humanitarian Affairs (UN-OCHA) reported in 2019 that floods severely disrupted socioeconomic development and community livelihoods, affecting over 570,000 people across Ethiopia. In response to these growing threats, reliable flood frequency information is critical for implementing early warning systems and designing effective flood protection infrastructures in flood-prone areas (Pandey et al., 2022; Yadav et al., 2024).

As highlighted in several studies, flood occurrences have shown an increasing trend in various areas due to the combined effects of changes in land use/land cover (LULC) and climate (Dutta et al., 2003; Fofana et al., 2022; Irannezhad et al., 2018; Saksena et al., 2019). LULC changes resulting from deforestation, agricultural expansion, and urbanization lead to an increase in surface runoff by altering the hydrologic characteristics of basins and watersheds (Cuo, 2016; Kundu & Olang, 2011). To assess the past conditions of watersheds and basins, historical LULC maps generated from remotely sensed images have been extensively utilized in several studies (Getachew & Manjunatha, 2022; Irannezhad et al., 2018; Mewded et al., 2021; Miller & Hutchins, 2017). Additionally, predicted LULC maps under different scenarios are crucial for understanding future hydrological conditions (Faichia et al., 2020; Gebresellase et al., 2023; Halmy et al., 2015). In this context, hybrid models such as the Cellular Automata-Markov (CA-Markov) model have been used in several studies, as this geospatial model integrates both the spatial and temporal prediction capabilities of the CA and Markov models (Arfasa et al., 2023; Leta et al., 2021a).

On the other hand, climate change contributes to flooding by altering the frequency, intensity, and duration of extreme rainfall events (Kim et al., 2021; Meresa et al., 2022; Yan et al., 2016). To assess the impact of climate change on extreme rainfall, general circulation models (GCMs) from the Coupled Model Intercomparison Project Phases 5 and 6 (CMIP5 and CMIP6) play crucial roles (Almazroui et al., 2020; Taylor et al., 2012). However, these models often exhibit biases due to their coarse spatial resolution, underlying assumptions, and boundary conditions (Famien et al., 2018; Michelangeli et al., 2009; Shiru et al., 2019). To reduce the biases of GCMs, the use of high-resolution downscaled outputs,

such as those from the NASA Earth Exchange-Global Daily Downscaled Projections (NEX-GDDP) dataset, is generally recommended (Jose & Dwarakish, 2022; Thrasher et al., 2022). In addition, biases associated with climate models can be reduced by evaluating and selecting the best-performing models from multiple GCMs and implementing bias correction methods (Enayati et al., 2021; Sharma & Kale, 2022; Srinivasa Raju et al., 2017; Srinivasa Raju & Nagesh Kumar, 2015).

Flood frequency analysis under changing climate and LULC conditions provides crucial insights for designing safe and cost-effective flood protection structures, thereby minimizing the destructive impacts of flooding on the environment, as indicated in several studies (Baky et al., 2020; Emam et al., 2016; Yisehak, 2021). This analysis can be conducted via statistical methods and rainfall-runoff models. Statistical flood frequency analysis involves estimating flood quantiles by applying the best-fitting probability distribution, which is based on the assumption that historical discharge time series are stationary and independent (Hosking & Wallis, 1997). On the other hand, rainfall-runoff models simulate the transformation of rainfall into runoff, considering various factors such as topography, soil characteristics, and land use (Mareuil et al., 2007; Noori et al., 2016; Yisehak, 2021).

Floods mostly occur at specific downstream reaches of the main river. Therefore, before flood protection structures are constructed, quantifying the contribution of upstream subwatersheds to peak flood magnitude, a process known as flood source area identification (FSAI), is often recommended (Saghafian & Khosroshahi, 2005). According to a comprehensive review provided by Singh et al. (2021), FSAI can be conducted via multicriteria evaluation (MCE) and the unit flood response (UFR) approach. The MCE approach can be implemented via geographic information systems (GISs), which consider the linear combination of weights from several flood-controlling factors without accounting for flow routing through river networks (Argaz et al., 2019; Elkhachy, 2015). In contrast, the UFR approach uses hydrological models to account for flow routing through rivers (Saghafian & Khosroshahi, 2005; Singh et al., 2021).

Like FSAI, flood inundation mapping plays a crucial role in providing information about areas susceptible to flooding, as well as in developing effective flood protection and risk management strategies (Heimhuber et al., 2015; Tiwari et al., 2020). Recently, synthetic aperture radar (SAR)-derived flood inundation mapping has emerged as a powerful approach (Elkhachy et al., 2021; Kumar et al., 2022; Tay et al., 2020). This approach allows for the detection of flooded areas via various algorithms, including fuzzy logic, active contour, change detection, and thresholding (Amitrano et al., 2024; Clement et al., 2018a; Nobre et al., 2016; Otsu, 1975). Among these algorithms, the change detection method is the most widely used, as it can be implemented in the Google Earth Engine (GEE)

cloud-based platform by comparing preflood and postflood images. Several studies (Kumar et al., 2022; G. Singh & Rawat, 2024; Tay et al., 2020) have demonstrated the effectiveness of the GEE-based change detection approach for both small- and large-scale flood inundation mapping.

For comprehensive flood hazard assessments, it is important to map flood depth, velocity, and water surface elevation in addition to flood inundation extent, which can be detected on the basis of SAR-based flood mapping. For this purpose, the Hydrologic Engineering Center-River Analysis System (HEC-RAS), developed by the US Army Corps of Engineers, is the most widely used model (Anuthaman et al., 2023; Dimitriadis et al., 2016; Thakur et al., 2017; Yadav et al., 2024). Previous studies (Costabile et al., 2020; Ongdas et al., 2020) have demonstrated the importance of the HEC-RAS two-dimensional (2D) model for flood hazard mapping. Moreover, recent studies (Elkhrachy et al., 2021; Ezzine et al., 2020; Psomiadis et al., 2020) have recommended combining SAR-derived data with the HEC-RAS 2D hydrodynamic model for effective flood inundation mapping.

In Ethiopia, floods frequently occur across various regions during the main rainy season (Sinshaw et al., 2018). This season typically spans from June to September, during which major rivers and their tributaries experience peak discharges. As a result, many rivers overflow and inundate adjacent areas and floodplains. The downstream reach of the Gumara River, which is part of the Upper Blue Nile (UBN) Basin, is one such area that is frequently affected by flooding due to the overflow of the Gumara River (Alemu & Assaye, 2020; Melkamu et al., 2022; Nigusie et al., 2021).

For this reason, this study aims to evaluate the combined impacts of LULC and climate changes on flood occurrence to support improved flood risk management strategies. To achieve this goal, various spatiotemporal datasets were utilized, including observed hydroclimatic records, climate model outputs, gridded rainfall products (GRFPs), LULC maps, soil data, and topographic information. The data analysis involved an integrated approach that combined statistical analysis, GEE, hydrologic and hydraulic modelling, and geospatial analysis tools.

1.2. Problem Statement

Floods are among the most devastating natural disasters, causing significant damage to infrastructure and disrupting the livelihoods of communities (Baky et al., 2020). According to the Intergovernmental Panel on Climate Change Report 6 (IPCC, 2021), climate change has intensified the frequency, magnitude, and intensity of water-related hazards. This is especially concerning in East Africa, where limited adaptive capacity amplifies the adverse impacts of such hazards (Taye & Dyer, 2024). In Ethiopia, particularly in the Gumara watershed of the UBN Basin, flooding frequently results in the

displacement of communities and the loss of agricultural crops (Alemu & Assaye, 2020; Melkamu et al., 2022).

Climate models from the CMIP5 and CMIP6 provide essential data for simulating extreme rainfall indices (ERFIs). However, evaluating and selecting the best-performing models from the available models remains critical (Raju & Kumar, 2020). While some studies in the UBN basin have assessed the performance of climate models in reproducing mean climatology (Alaminie et al., 2021; Mohammed, 2024), limited research has been conducted to evaluate their performance in capturing ERFIs. This gap hinders reliable analysis of future climate extremes, which is essential for understanding their impact on future flood risks.

In the Gumara watershed, significant changes in LULC, particularly in forest, grassland, and shrubland areas, have occurred due to deforestation, agricultural expansion, settlement growth, and overgrazing (Bogale, 2020). These changes could alter surface runoff generation processes, thereby influencing flood risk. Several studies have investigated historical LULC changes in watersheds (Chakilu & Moges, 2017; Wubie et al., 2016), mostly via the maximum likelihood (ML) classification method. However, limited attention has been given to advanced machine learning classifiers, such as random forest (Breiman, 2001). Recent studies have recommended the use of RF classifiers via the GEE platform for more accurate LULC mapping (Kadri et al., 2023; Noi Phan et al., 2020; Shafizadeh-Moghadam et al., 2021). Moreover, most existing studies focus on historical LULC conditions, with little emphasis on future LULC dynamics under different scenarios. This limitation restricts flood frequency analysis under projected land use conditions, which is critical for effective flood risk management. Therefore, predicting future LULC patterns in the Gumara watershed under different scenarios is vital for supporting flood frequency assessments.

Flood protection measures such as levees, floodwalls, dams, and diversion channels are widely used to mitigate flood risk. However, constructing these structures across an entire watershed is often impractical because of their high cost. Therefore, identifying and prioritizing subwatersheds on the basis of their contribution to peak flooding is essential for the strategic placement of water conservation structures (Saghafian & Khosroshahi, 2005). Although previous studies in the Gumara watershed have addressed flood hazard mapping (Melkamu et al., 2022; Nigusie et al., 2021), limited attention has been given to ranking subwatersheds by their flood contributions.

Traditional flood mapping methods rely primarily on ground-based observations at the time of flooding, which are labor intensive and time consuming (Elkhrachy et al., 2021). In contrast, SAR-derived flood mapping offers a faster and more efficient alternative (Kumar et al., 2022; Tiwari et al.,

2020). However, downloading, storing, and processing SAR imagery demands significant data storage and computational resources (Passah et al., 2023), which can hinder its broader application. To address this, recent studies have recommended the use of the GEE cloud-based platform (Gorelick et al., 2017) for efficient flood inundation mapping. While SAR-derived flood extent maps provide near-real-time spatial coverage, they are also critical for simulating flood depth, velocity, and water surface elevation. The 2D hydrodynamic HEC-RAS model is widely recommended for this purpose (Costabile et al., 2020; Vashist & Singh, 2023). Nonetheless, the lack of calibration and validation data limits its application for comprehensive flood inundation mapping. To address this challenge, SAR-derived flood maps can be used to calibrate and validate hydrodynamic model outputs (Ezzine et al., 2020; Psomiadis et al., 2020).

1.3. Research objective

This study aims to evaluate the combined impacts of LULC and climate change on flood occurrence in the Gumara watershed, UBN basin of Ethiopia.

The specific objectives of the study are as follows:

- To evaluate and compare the performances of the CMIP5 and CMIP6 climate models in reproducing extreme rainfall events in the UBN basin;
- To detect historical LULC changes and predict future LULC dynamics under different scenarios in the Gumara watershed;
- To assess the combined impacts of LULC and climate changes on flood frequency and identify potential flood source areas within the Gumara watershed;
- To analyse the influence of LULC and climate changes on flood inundation patterns in the downstream areas of the Gumara watershed;

1.4. Research Question

- How accurately do the CMIP5 and CMIP6 climate models simulate extreme rainfall events in the UBN basin?
- What are the historical and projected LULC changes in the Gumara watershed, and how do different scenarios influence these dynamics?
- How do combined changes in climate and LULC affect flood frequency, flood source areas, and flood inundation patterns in the Gumara watershed?

1.5. Scope and Limitations of the Study

From a geographic scope perspective, analyses of extreme rainfall events (first objective) was conducted at the basin scale in the UBN basin. In contrast, the remaining objectives, including LULC change analysis and prediction, FSAI, and flood inundation mapping, were carried out at the watershed scale in the Gumara watershed. The temporal scope of the analysis encompasses the observation period (1981–2019), the baseline period for climate model simulations (1981–2005), the future projection period (2031–2080), and SAR-based flood inundation mapping (2017–2021). A multidisciplinary methodological framework was employed, integrating remote sensing, hydrological and hydraulic modelling, and scenario-based analysis to assess flood dynamics under changing LULC and climate conditions. Climate projections from the CMIP5 and CMIP6 models were used to estimate future extreme rainfall, and future LULC scenarios were developed under business-as-usual (BAU) and governance (GOV) assumptions via a CA-Markov model. The HEC-HMS and HEC-RAS models were used to simulate runoff generation and flood inundation, respectively, whereas the GEE platform facilitated rapid flood mapping via Sentinel-1 SAR imagery. This study applied the UFR approach to identify flood source areas and rank subwatersheds on the basis of their contribution to peak discharge.

Despite its comprehensive and integrative approach, this study has several limitations. Although multimodel ensembles from CMIP5 and CMIP6 have been employed to reduce uncertainties in climate projections, inherent limitations in GCMs and downscaling techniques remain a challenge for reliably estimating future extreme rainfall events. The LULC projections were developed on the basis of generalized future scenarios, which may not fully capture the complexity of socioeconomic and policy dynamics. Additionally, the digital elevation model (DEM) used for terrain processing in HEC-RAS, with a 12.5-meter spatial resolution, lacked a detailed representation of riverbed features. This limitation necessitated manual modification using cross-sectional data, which may have affected the accuracy of the predicted flood extents.

1.6. Significance of the Study

The significance of this study lies in its comprehensive assessment of the impacts of LULC and climate changes on flood occurrence in the Gumara watershed, a flood-vulnerable area within the UBN basin of Ethiopia. As the frequency and intensity of flood events continue to rise in a region, understanding the underlying drivers becomes increasingly vital. This research offers critical insights by integrating hydrological (HEC-HMS) and hydraulic (HEC-RAS) modelling techniques with satellite-based flood mapping via the GEE platform. By incorporating scenario-based analyses of projected LULC and climate changes, this study provides a robust methodological framework for evaluating future flood

risks. The results are particularly relevant for informing policy decisions and promoting sustainable watershed management. Additionally, this study addresses a significant gap in the literature by offering an integrated analysis of flood dynamics under changing environmental conditions. Through its interdisciplinary approach, this study can support planners, decision-makers, and environmental managers in designing effective adaptation and mitigation strategies for flood-prone watersheds.

1.7. Structure of the dissertation

This dissertation consists of seven chapters. It begins with an introductory chapter that presents the problem statement, research objectives and questions, scope and limitations, and significance of the study. Chapter 2 outlines the overall methodological framework of the study. The four specific objectives of the research are addressed individually in Chapters 3 through 6. Each chapter includes an introduction, materials and methods, results and discussion, and conclusions. Finally, Chapter 7 provides conclusions and recommendations, summarizes the main findings of the study and suggests directions for future research.

CHAPTER 2

2.1. Overall Methodology of the Study

The overall methodology of the study was designed to comprehensively evaluate how combined LULC and climate changes influence flood occurrence, magnitude, and inundation extent in the Gumara watershed, which is part of the UBN basin, Ethiopia. The study employed a multidisciplinary approach that integrated climate model evaluation, remote sensing-based LULC classification and prediction, hydrological and hydraulic modeling, and flood inundation mapping under various future scenarios.

The first part of the study focused on evaluating the performance of climate models in reproducing historical extreme rainfall events. For this, a total of sixteen GCMs, eight from the Coupled Model Intercomparison Project Phase 5 (CMIP5) and eight from Phase 6 (CMIP6), were assessed using merged rainfall data from 1981 to 2005. Extreme rainfall indices (ERFIs), as defined by the Expert Team on Climate Change Detection and Indices (ETCCDI), were computed for both observed and simulated datasets. The statistical performance of each climate model was evaluated using the Pearson correlation coefficient (R), root mean square error (RMSE), and percent bias (PBIAS). The models were then ranked using the multi-criteria Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) approach. The four best-performing models from each CMIP phase were selected for future projections. These selected models underwent bias correction to minimize systematic errors. Future extreme rainfall scenarios for the periods 2031–2055 and 2056–2080 were then projected using these bias-corrected GCM ensembles under Representative Concentration Pathways (RCP4.5 and RCP8.5) and Shared Socioeconomic Pathways (SSP2-4.5 and SSP5-8.5).

The second part of the study involved the detection of historical LULC changes and the prediction of future LULC dynamics. Historical LULC classification was conducted for the years 1985, 2000, 2010, and 2019 using Landsat imagery processed in the Google Earth Engine (GEE) platform. The Random Forest machine learning classifier was employed to classify the images into various land cover types such as forest, shrubland, grassland, cultivated land, and settlements. The classification outputs were validated using accuracy assessment metrics such as overall accuracy (OA), user's accuracy (UA), producer's accuracy (PA), and the Kappa coefficient (K). Future LULC scenarios for the years 2035 and 2065 were predicted using the Cellular Automata–Markov (CA–Markov) model under two scenarios: Business-as-Usual (BAU) and Governance (GOV). The BAU scenario assumed the continuation of historical trends, while the GOV scenario represented a sustainable land management approach.

The third part of the study focused on hydrological modeling to simulate rainfall-runoff processes and analyze the impact of LULC and climate changes on flood occurrence. The Hydrologic Engineering Center-Hydrologic Modeling System (HEC-HMS) version 4.11 was applied to model the rainfall-runoff transformation for various return periods (5, 10, 25, 50, and 100 years). Design rainfall depths for short durations were generated from the 24-hour design rainfall values using a depth-duration-frequency (DDF) relationship. The rainfall-runoff model was calibrated and validated using observed streamflow data from historical flood events. In addition to simulating flood hydrographs, Flood Source Area Identification (FSAI) was conducted using the Unit Flood Response (UFR) approach, which helped to identify and rank subwatersheds based on their relative contributions to peak flood discharges. This analysis provided crucial information for prioritizing flood mitigation efforts in upstream areas.

The fourth part of the study addressed flood inundation mapping to assess flood extents and depths in downstream areas of the Gumara watershed. This component combined remote sensing and hydraulic modeling approaches. Sentinel-1 Synthetic Aperture Radar (SAR) images were processed using the GEE cloud computing platform to rapidly map flood extents using a change detection approach. This approach compared pre-flood and post-flood SAR images to delineate flooded areas during historical flood events (2017–2021). These SAR-derived flood extent maps were then used to calibrate and validate the Hydrologic Engineering Center-River Analysis System (HEC-RAS) 2D unsteady flow hydraulic model. The hydraulic model used a modified terrain model from a 12.5-meter DEM. Using calibrated boundary conditions, the HEC-RAS model simulated flood depths, velocities, and inundation extents for various historical and future climate-LULC scenarios. The flood hazard classification was also performed based on depth and velocity criteria to delineate high-risk areas.

Finally, the methodology integrated the results of the climate, LULC, hydrologic, and hydraulic analyses to comprehensively assess the combined impacts of climate and land cover changes on flood hazards in the Gumara watershed. This integrated assessment revealed how projected changes in rainfall extremes and land cover dynamics would influence peak discharge, runoff volume, and flood inundation extents across different return periods and future scenarios. The methodology provided valuable insights for flood risk management and watershed conservation planning, offering a scientific basis for designing flood mitigation strategies and land management policies under future environmental change scenarios. Overall, this comprehensive methodological framework not only addressed the complex interactions between climate change, land use dynamics, and hydrological

processes but also demonstrated an integrated approach for flood hazard assessment in other similar regions experiencing rapid environmental and climatic transformations.

2.2. Conceptual Framework of the Study

The conceptual framework of the study integrates multiple methodological components to assess the impacts of LULC and climate changes on flood occurrence. The study is structured around four interlinked objectives, each contributing to the comprehensive assessment of flood risks under changing environmental conditions. Figure 2.1 below illustrates the overall conceptual framework and the interlinkages between the objectives of the study.

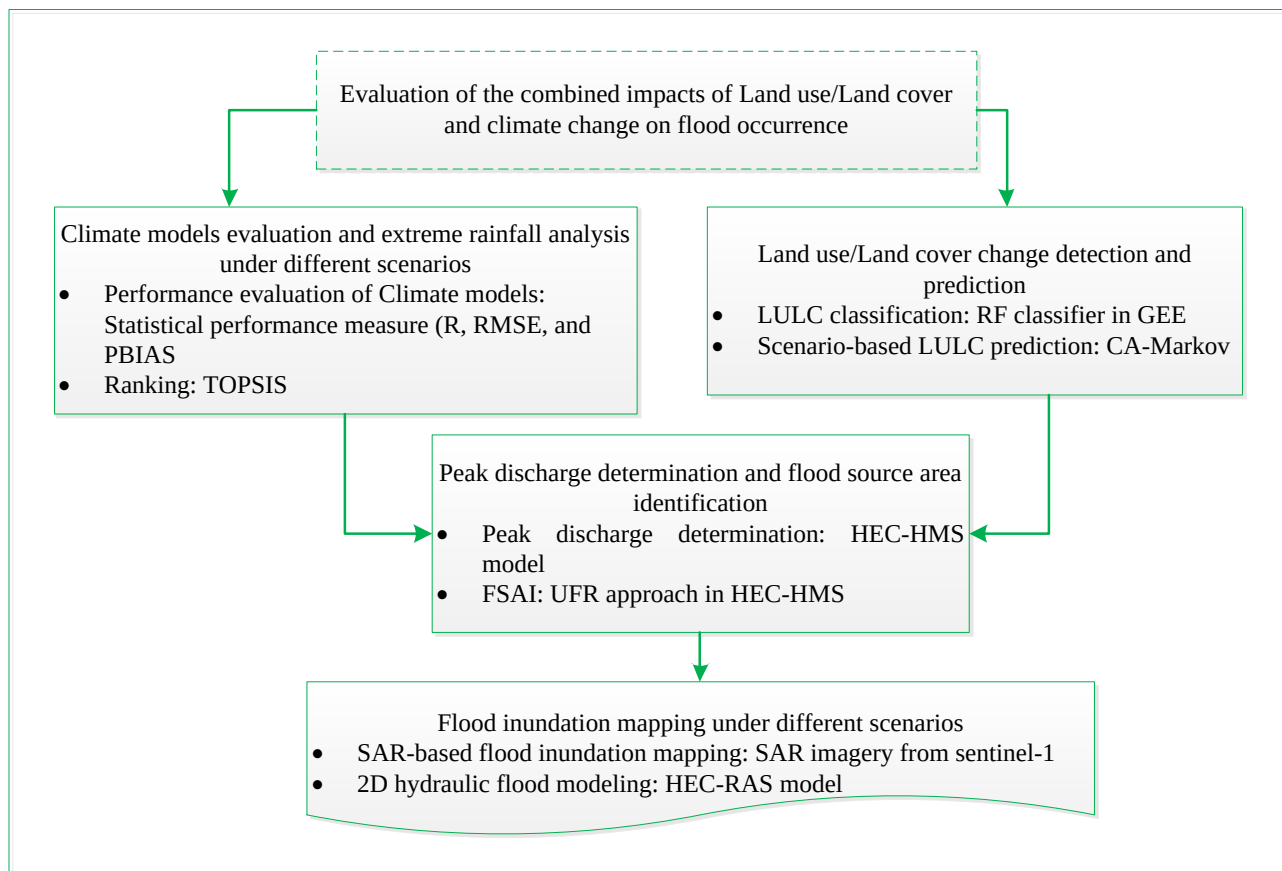


Figure 2. 1: Overall conceptual framework of the study

CHAPTER 3

3. Evaluation and comparison of the performances of the CMIP5 and CMIP6 models in reproducing extreme rainfall in the Upper Blue Nile basin of Ethiopia

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Abstract

Understanding the characteristics of extreme rainfall is vital for planning effective adaptation and mitigation measures. Thus, this study aims to evaluate the performances of 16 general circulation models (GCMs) of the coupled model intercomparison project (8 CMIP5 and 8 CMIP6) in reproducing observed extreme rainfall indices (ERFIs) and monthly rainfall in the Upper Blue Nile (UBN) basin of Ethiopia (1981–2005). The observed ERFIs were computed based on rainfall estimates of the random forest merging (RF-MERGE) algorithm, which combines ground-based rainfall with three gridded rainfall products (GRFPs). The GCMs were evaluated using statistical performance measures such as the Pearson correlation coefficient (R), root mean square error (RMSE), and percent bias (PBIAS). Using the Technique for Order Preferences by Similarity to an Ideal Solution (TOPSIS), the GCMs were ranked from least skilled to most skilled. Accordingly, MIROC5 of the CMIP5 and MPI-ESM1-2-LR of the CMIP6 models were found to be the most suitable models. Furthermore, the top-ranked models were selected and bias-corrected using quantile mapping (QM), and their ensembles (CMIP5-ensemble and CMIP6-ensemble) were used for projecting future extremes under representative concentration pathways (RCP4.5 and RCP8.5) and shared socioeconomic pathways (SSP2-4.5 and SSP5-8.5), respectively, for the periods 2031–2055 and 2056–2080. Most of the ERFIs exhibited high variability and inconsistent trends for both the observations and future periods. The findings of this study provide valuable insights into the impacts of climate change on ERFIs, and the developed framework can serve as a reference for future research.

Keywords: CMIP5; CMIP6; extreme rainfall indices; RF-MERGE; TOPSIS; variability and trends; UBN basin of Ethiopia.

3.1. Introduction

Climate change is one of the most important concerns attracting the attention of experts and government policymakers (Sayadi et al., 2019). Recently, the increase in greenhouse gas emissions

has resulted in a climatic imbalance in the Earth's atmosphere (Alehu et al., 2022; Althor et al., 2016; Pachauri et al., 2014; Toride et al., 2018). According to the Intergovernmental Panel on Climate Change (IPCC) report (2013), this climatic imbalance may change the frequency, intensity, and duration of climate-related extremes. Tabari (2020) stated that climate-related extremes, especially extreme rainfall events, intensify the occurrence of floods. As a result, floods could have a negative impact on the livelihood of the community and the environment in general (Khoi et al., 2021). In this regard, as indicated in Gebrechorkos et al. (2019), Africa can be considered the most vulnerable region to climate-related extremes due to its weak adaptation capacity.

General circulation models (GCMs) are the main tools for simulating historical and future climate patterns and extremes. These models are numerical representations of the Earth's climate system developed based on physical laws and empirical relations of processes in the ocean, atmosphere, and land surface (Raju & Kumar, 2020). Among the GCMs, the Coupled Model Intercomparison Project (CMIP) is the most widely applied for climate change studies (Eyring et al., 2016; Taylor et al., 2012). However, the outputs of these GCMs are associated with large inherent uncertainties due to model assumptions, initial and boundary conditions, coarse spatial resolution, parameterization, model structure, calibration, and other factors (Jose & Dwarakish, 2022). To overcome these uncertainties, it is mostly recommended to downscale coarse-resolution GCMs to fine resolutions using different types of statistical and dynamical downscaling approaches (Gebrechorkos et al., 2023; Noël et al., 2021). Moreover, as indicated in several studies, these uncertainties can be minimized through the evaluation and selection of appropriate GCMs before applying output models for climate-related studies (Lun et al., 2021). In this regard, the evaluation and selection of GCMs can be implemented by comparing historical GCM simulations with observed data (Sharma & Kale, 2022).

Several studies have evaluated the performance of CMIPs in reproducing the extreme rainfall indices (ERFIs) recommended by the Expert Team on Climate Change Detection and Indices (ETCCDI) (Tank et al., 2009). For example, Jiang et al. (2015) evaluated the performance of 31 GCMs of CMIP5 in reproducing ERFIs across China, finding high interannual variability in indices such as RF on extremely wet days (R99p) and annual total wet-day rainfall (PRCPTOT). Tang et al. (2021) conducted a quantitative evaluation of the performances of 40 CMIP6 models in reproducing PRCPTOT, R99p, consecutive dry days (CDD), and the simple daily intensity index (SDII). In their study, the authors found different model performances for each of the ERFIs. Similarly, Chen et al. (2021) evaluated and compared the performances of 28 CMIP5 and 30 CMIP6 models in reproducing seasonal ERFIs over the western North Pacific and East Asia and reported that the CMIP6 models better captured the annual

maximum 1-day rainfall (RX1day), annual maximum consecutive 5-day rainfall (RX5day), and R99p than did the CMIP5 models.

As discussed above, most of the reviewed studies are highly concentrated on evaluating the performances of GCMs in simulating ground-based observed ERFIs. However, ERFIs that can be computed using ground-based rainfall measurements are susceptible to uncertainty due to the sparse distribution of rain gauges, short-term records, numerous data gaps, the effect of topography, the improper design of rain gauges, and other environmental factors (Cauteruccio et al., 2021; Molini et al., 2005). To address these issues, gridded rainfall products (GRFPs), such as the Climate Hazards Group InfraRed Precipitation with Station (CHIRPS), Multi-Source Weighted-Ensemble Precipitation (MSWEP), and Enhanced Global Dataset for the Land Component of the Fifth Generation of European Reanalysis (ERA5-Land), can provide alternative long-term spatiotemporally distributed rainfall products (Beck et al., 2017; Funk et al., 2015; Guermazi et al., 2019; Muñoz-Sabater et al., 2021). However, rainfall data from GRFPs are still prone to systematic bias associated with the assumptions of numerical estimation algorithms used to generate rainfall products (Iqbal et al., 2022). For these reasons, recent studies have recommended merging ground-based rainfall with GRFPs using robust merging algorithms such as the random forest merging algorithm (RF-MERGE) to improve the quality of rainfall data (Baez-Villanueva et al., 2020; Belay et al., 2022).

In Ethiopia, some previous studies have been conducted on the performance evaluation of GCMs and regional climate models (RCMs) in capturing climatic variables such as monthly rainfall (Dibaba et al., 2019; Mengistu et al., 2021). For example, Alaminie et al. (2021) evaluated the performance of 12 CMIP6 GCMs in capturing the mean climatology of the Upper Blue Nile (UBN) basin using statistical performance measures. However, this study did not explicitly provide the ranks of GCMs based on their performances. For the explicit ranking of GCMs, recent studies have recommended the application of multiple-criteria decision-making (M-CDM) approaches (Jose & Dwarakish, 2022). Moreover, in Ethiopia, extreme rainfall events are considered major causes of climate-related extremes (Addisu et al., 2015; Bulti et al., 2021; Dawit et al., 2019; Mekasha et al., 2014). For this reason, a number of studies have been conducted on the variability and trends of ERFIs in different parts of the country using long-term observed rainfall data. However, these studies focused on the variability and trends of historical extremes based on observed rainfall data, and less attention was given to future extremes. In this case, studies by Bulti et al. (2021) and Khoi et al. (2021) recommended the investigation of climate change impacts on ERFIs.

Hence, this study evaluates and compares the performances of 8 CMIP5 and 8 CMIP6 GCMs of the NEX-GDDP datasets in reproducing observed ERFIs and monthly rainfall computed based on RF-

MERGE rainfall estimates in the Upper Blue Nile (UBN) basin of Ethiopia. In this study, the ERFIs, which are indicators of flood disasters (consecutive wet days (CWD), PRCPTOT, number of very heavy rainfall events (R20), rainfall events on very wet days (R95p), R99p, RX1day, RX5day, and SDII), were considered since the basin is highly vulnerable to climate-related extreme events. In this study, the CMIP5 and CMIP6 models were ranked based on their performance, and then bias-corrected ensembles of the most skilled models were used to project future extremes. Finally, the changes, trends, and variability of the ERFIs were analyzed for both historical and future periods.

3.2. Materials and Methods

3.2.1. Study Area

This study was conducted in the Upper Blue Nile (UBN) basin of Ethiopia, which is located in the northwestern part of Ethiopia (Figure 3.1). The UBN basin lies between 7° 45' N and 12° 45' N latitude and 34° 05' E and 39° 45' E longitude, with a drainage area of 176,652 square kilometers, which accounts for approximately 17% of the total area of Ethiopia (Conway, 2000). The UBN River is the main source of the Nile River, which originates in Gish Abbay in West Gojam and runs northwest to the Sudanese border with a length of approximately 940 km, finally joining the White Nile at Khartoum, Sudan (Yilma & Awulachew, 2009). The basin contributes approximately 70% (48.5 billion m³/year) of the total annual flow volume to the Nile River (Nawaz et al., 2010). The UBN basin is characterized by complex topographic features such as hills, mountains, valleys, rivers, and escarpments (Awulachew et al., 2009; Worku et al., 2019). Elevations within the basin range from 483 to 4266 meters above mean sea level (amsl) (Figure 3.1c).

The climatic conditions of the UBN basin are significantly controlled by elevation and the movement of the Intertropical Convergent Zone (ITCZ) (Nawaz et al., 2010). The rainfall in the basin is characterized by a high degree of variability, with three main seasons: (1) a rainy season, or “Kiremt,” which occurs from June to September and contributes more than 70% to the annual rainfall of the basin; (2) a dry season, or “Bega,” which occurs from October to January; and (3) a short rainy season, or “Belg,” which occurs from February to May (Endalew, 2007; Worku et al., 2019). In general, the mean annual rainfall ranges between 1200 and 1800 mm, with an increasing gradient from the northeast to the southwest part of the basin (Ayehu et al., 2021). The long-term mean annual temperature of the basin is approximately 18.5 °C, with a small seasonal variation of less than 2 °C (Kim & Kaluarachchi, 2009). In the basin, vertisols and nitisols are the dominant soil types, and rain-fed agricultural cultivation accounts for more than 60% of the land use in the basin (Awulachew et al., 2009; Tikuye et al., 2023).

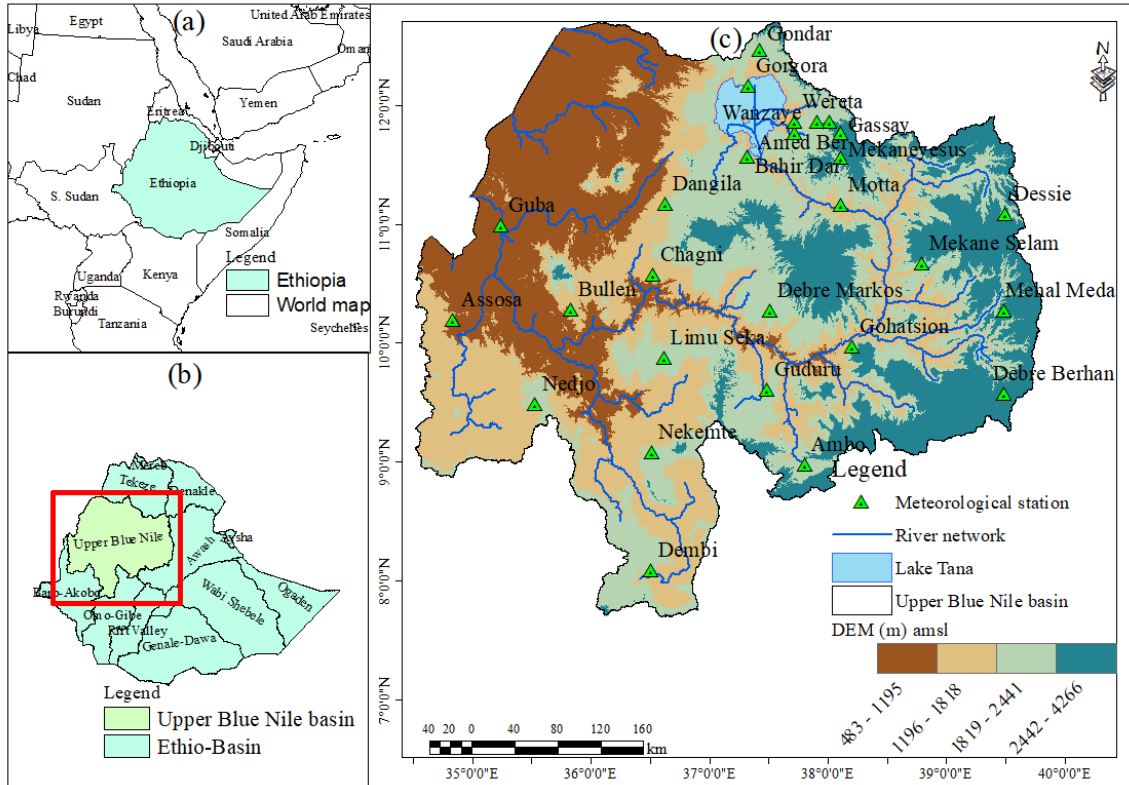


Figure 3.1. Location map of the study area. (a) Location map of Ethiopia within the Africa context; (b) river basins of Ethiopia; and (c) meteorological stations, river network, and elevation map of the Upper Blue Nile basin.

3.2.2. Datasets

3.2.2.1. Ground-based and Gridded Rainfall Data

Daily ground-based rainfall data recorded in the UBN basin were collected from the National Meteorological Agency (NMA) of Ethiopia at 27 meteorological stations from 1981 to 2019. The ground-based stations were selected based on the availability of long-term rainfall records with a minimum number of missing data points. Details of the ground-based rainfall stations situated within the UBN basin of Ethiopia including latitude and longitude, elevation, and mean annual rainfall for each station are presented in Appendix A1.

In areas with complex topography, such as the UBN basin of Ethiopia, sparsely distributed ground-based rainfall may not adequately capture rainfall patterns. To overcome this problem, three GRFPs, (1) CHIRPS V2, (2) MSWEP V2.8, and (3) ERA5-Land, were merged with ground-based rainfall data. The GRFPs considered in this study were selected based on the availability of long-term rainfall data and due to their better performance in capturing the rainfall pattern of the UBN basin following previous studies (Ayehu et al., 2018; Gashaw et al., 2023; Lakew et al., 2020).

CHIRPS is a high-resolution, quasi-global daily rainfall product that combines satellite data with ground-based observations (Funk et al., 2015). This product provides daily rainfall estimates with a spatial resolution of 0.05° (5 km) from 1981 to the present. CHIRPS data can be freely accessed from the Climate Hazards Group website (<https://www.chc.ucsb.edu/data/chirps>). MSWEP is a global rainfall product based on ground-based, satellite, and reanalysis data, and it is available from 1979 to the present (Beck et al., 2017). For this study, MSWEP data with daily temporal resolution and 0.1° spatial resolution were obtained from the <https://www.gloh2o.org/> website. ERA5-Land provides daily reanalysis rainfall data derived from a combination of ground-based and atmospheric models and satellite data with a 0.1° (approximately 11.1 km) spatial resolution from 1981 to the present (Muñoz-Sabater et al., 2021). The dataset can be freely accessed from the European Centre for Medium-Range Weather Forecasts (ECMWF) website via <https://www.ecmwf.int/en/forecasts/datasets/reanalysis-datasets/era5-land>. For this study, CHIRPS and ERA5-Land at each observation station (point-pixel) were accessed using the Climate Engine cloud-based platform (<https://www.climateengine.org/>), while MSWEP data were extracted in a Python environment. For easy analysis of the GRFPs with ground-based data, daily rainfall data for all three GRFPs were obtained for the same period (from 1981 to 2019). In addition, the Shuttle Radar Topography Mission (SRTM) digital elevation model (DEM) (Farr et al., 2007) at a spatial resolution of 30 m was used for extracting elevation information for ground-based stations.

3.2.2.2 General Circulation Models

To understand possible historical and future climate patterns, a rainfall dataset of 8 statistically downscaled CMIP5 and 8 CMIP6 GCMs from the NEX-GDDP was used for the present study. For statistical downscaling, the NEX-GDDP used an observational dataset from the Global Meteorological Forcing Dataset (GMFD) with a 0.25° spatial resolution at daily time steps. The NEX-GDDP-CMIP5 dataset includes historical (1981–2005) and future (2031–2080) climate projections under representative concentration pathway (RCP) scenarios (RCP4.5 and RCP8.5). The NEX-GDDP-CMIP6 dataset includes the same historical period and future climate projections under shared socioeconomic pathway (SSP) scenarios (SSP2-45 and SSP5-85). Although CMIP5 historical simulations extend to 2005 and CMIP6 to 2014, for consistency in baseline comparisons, the historical period 1981–2005 was uniformly applied in this study.

All the downscaled outputs of the GCMs used for this study have an approximate spatial resolution of 0.25° , or $25 \text{ km} \times 25 \text{ km}$, and a daily temporal resolution. The dataset was downloaded via the Google Earth Engine (GEE) cloud-based platform. Table 3.1 presents a list of 8 CMIP5 and 8 CMIP6 GCMs downscaled by the NEX-GDDP (hereafter CMIP5 and CMIP6 models), along with their

horizontal resolutions, modeling centers, and countries of origin. For this study, the models were selected due to their better performance in simulating the RF characteristics of the UBNB basin of Ethiopia following previous studies (Alaminie et al., 2021; Bhattacharjee & Zaitchik, 2015; Tenfie et al., 2022). Models with runs r1i1p1f1 and r1i1p1f2 and models available in both NEX-GDDP-CMIP5 and CMIP-6 were considered for this study. In addition, for comparison of the raw and downscaled products, the raw climate model data from the selected CMIP5 and CMIP6 models were obtained from the Pierre Simon Laplace Institute (IPSL, <https://esgf-node.ipsl.upmc.fr/projects/esgf-ipsl/>).

Table 3.1. GCM names, resolutions, modeling centers, and countries for the CMIP5 (indicated in bold) and CMIP6 global climate models.

Sno.	GCM name	Horizontal resolution	Modeling center	Country
1	ACCESS1-0	1.30° × 1.90°	Organization and Bureau of Meteorology	Australia
2	ACCESS-CM2	1.25° × 1.67°		
3	CNRM-CM5	2.80° × 1.40°	Centre National de Recherches Meteorologiques	France
4	CNRM-CM6-1	1.40° × 1.40°		
5	MIROC5	1.40° × 1.40°	National Institute for Environmental Studies, the University of Tokyo	Japan
6	MIROC6	1.40° × 1.40°		
7	MPI-ESM-LR	1.90° × 1.90°	Max Planck Institute for Meteorology	Germany
8	MPI-ESM1-2-LR	1.87° × 1.86°		
9	MRI-CGCM3	1.10° × 1.10°	Meteorological Research Institute	Japan
10	MRI-ESM2-0	1.12° × 1.12°		
11	CanESM2	2.80° × 2.80°	Canadian Centre for Climate Modelling and Analysis	Canada
12	CanESM5	2.79° × 2.81°		
13	IPSL-CM5A-LR	3.70° × 1.90°	L'Institut Pierre-Simon Laplace	France
14	IPSL-CM6A-LR	2.50° × 1.27°		
15	BCC-CSM1-1	2.80° × 2.80°	Beijing Climate Center, China Meteorological Administration	China
16	BCC-CSM2-MR	1.10° × 1.10°		

3.2.3. Overall Methodology

This study focused on evaluating and comparing 16 GCMs for simulating ERFIs and monthly rainfall over the UBN basin of Ethiopia. The main procedures followed in this study are summarized as follows: First, the quality of the observed rainfall data was checked in terms of homogeneity and consistency. Second, the random forest merging (RF-MERGE) approach was used to merge ground-based rainfall data with the GRFP data. Third, average ERFIs and monthly rainfall over the study basin were estimated using rainfall estimates based on RF-MERGE and historical climate data from 16 GCMs. Fourth, to evaluate the performance of GCMs in reproducing observed extremes (computed based on RF-MERGE), statistical performance measures were computed. Fifth, using the M-CDM approach, GCMs were ranked based on their average skill score. Afterwards, the most skilled models (four models from CMIP5 and four models from CMIP6) were selected to construct an ensemble for the projection of future extremes and monthly rainfall under the RCP and SSP scenarios. Additionally,

an evaluation of downscaling and bias correction approaches and an evaluation of the relative performances of CMIP5 and the corresponding CMIP6 models were also performed along with the previously mentioned tasks. Finally, the percentage change, trends, variability, and correlation of the ERFIs were analyzed sequentially.

3.2.4. Data Quality Control

Climate-related studies require complete and homogeneous time series data for analysis (Tan et al., 2019). However, a considerable amount of meteorological time series data may be missing, and hence, the missing data need to be filled. For this study, inverse distance weighting (IDW) was used to fill in missing observed daily rainfall data. This method is preferable to fill in missing data, as discussed in several studies (Chinasho et al., 2021; Muluken Lebay, 2020). In addition to missing rainfall data, short-term daily rainfall records were found at some stations. To extend the short-term rainfall data for these stations, the maintenance of variance extension, type 1 (MOVE.1) approach was applied. The method was first proposed to extend streamflow records, as stated in Hirsch (1982), but later, other researchers, for example, Githungo et al. (2016), applied the method for short-term rainfall data extension and found better results. The method assumes a linear relation between the concurrent rainfall record periods at the short-term and long-term (index) stations (Bastola & François, 2012).

Once the missing rainfall data were filled and the short-term rainfall data were extended, a homogeneity test was applied to detect significant change points in the annual rainfall data using the nonparametric Pettitt (1979) test. This test has been extensively applied and recommended for change point detection in many studies (Waghaye et al., 2018; Yisehak, 2021). For this study, the Pettitt test was performed using the “Nonparametric trend tests and change-point detection” R package (Pohlert, 2016). Based on this test, the annual rainfall values of most of the stations in this study were found to be homogeneous, and some inhomogeneous stations were corrected to ensure consistency.

3.2.5. Random Forest Merging (RF-MERGE)

In this study, improved daily rainfall data were generated using the random forest (RF) merging approach (RF-MERGE). The RF algorithm is a supervised machine learning approach for both classification and regression problems that involves the construction of multiple decision trees (Breiman, 2001). The algorithm is capable of handling high-dimensional data and requires a minimum number of parameters (Baez-Villanueva et al., 2020; Fan et al., 2021). The process of merging generally involves the selection of bootstrap samples from given training data, the construction of multiple decision trees, and the computation of the final output by averaging the outputs of multiple decision trees. In this study, the three gridded rainfall products and elevation information were used as

independent variables, and ground-based rainfall was used as a dependent variable for constructing decision trees. The merging procedure was performed using the “*randomForest*” R package (Breiman, 2018). Similar to other machine learning algorithms, the RF algorithm requires more training data than testing data. This allows the algorithm to learn complex relationships between the dependent variable (ground-based rainfall) and the independent variables (GRFPs and elevation information) (Baez-Villanueva et al., 2020). For this reason, 20 stations (approximately 70% of the stations) were used for training, and the remaining 7 stations were used for testing. The training stations were also selected from diverse climatologies and topographies to increase the prediction capability of the algorithms. To improve the accuracy of merging in the RF algorithm, parameters such as the minimum number of bootstrap samples (n_{min}), the number of trees (n_{trees}), and the number of features ($n_{features}$) at the splitting node are the most important parameters. In this study, n_{min} , n_{trees} , and $n_{features}$ were estimated to be 6, 250, and 3, respectively, based on trial-and-error processes and considering parameters used by previous studies (Fan et al., 2021; Nguyen et al., 2021).

Furthermore, to show the superiority of RF-MERGE, two other merging approaches, averaging (AVG) and linear regression (LR) models, were considered. The AVG approach simply considers the average of three gridded rainfall products to estimate the final merged product, while the LR approach works by establishing a linear regression model between the ground-based rainfall (a dependent variable) and the gridded rainfall products (independent variables).

3.2.6. Performance Evaluation of Gridded Rainfall Products and Merged Rainfall Estimates

To evaluate the performance of the GRFPs and the three merging approaches discussed above, statistical and categorical performance measures were considered. Based on this, the Pearson correlation coefficient (R), root-mean-square error ($RMSE$), and percent of bias ($PBIAS$) were selected from the statistical performance measures. R was selected for evaluating the strength of the linear relationship, $RMSE$ to check the estimation accuracy, and $PBIAS$ for measuring the bias associated with the GRFPS and merging approaches compared to ground-based rainfall. Equations 3.1-3.3 show the expressions for R , $RMSE$, and $PBIAS$, respectively.

$$R = \frac{\sum(o_i - \bar{o})(m_i - \bar{m})}{\sqrt{\sum(o_i - \bar{o})^2} \sqrt{\sum(m_i - \bar{m})^2}} \quad (3.1)$$

$$RMSE = \left(\frac{1}{N} \sum(o_i - m_i)^2 \right)^{0.5} \quad (3.2)$$

$$PBIAS = \frac{\sum(m_i - o_i)}{\sum o_i} \times 100 \quad (3.3)$$

where m_i is the i^{th} value of daily rainfall estimates (based on GRFPs or merging approaches) and o_i is the i^{th} value of ground-based daily rainfall data. $\bar{m}$ and $\bar{o}$ are the means of the daily rainfall based on rainfall estimates and ground-based rainfall, respectively. N is the number of data points. R ranges from -1 to 1 (inclusive), with an optimal value of 1, indicating a perfect positive linear relationship. $RMSE$ (mm) ranges from 0 to $+\infty$, with an optimal value of 0, indicating perfect agreement with no error. $PBIAS$ (%) ranges from $-\infty$ to $+\infty$, with an optimal value of 0, indicating no bias.

From the categorical performance measures, the probability of detection (POD), false alarm ratio (FAR), and critical success index (CSI) were selected to evaluate the performance of the GRFPs and the outputs of the merging approaches in detecting rainy and nonrainy days with a threshold of 1 mm/day (Ghorbanian et al., 2022; Liemohn et al., 2021). The POD measures the ratio of the number of events correctly detected by the GRFPS and the merging approaches to the total number of events identified by the ground-based station. The FAR quantifies the percentage of rainfall events detected by the GRFPs and merging approaches but is not confirmed by the ground-based station. The CSI combines POD and FAR to quantify the overall performance of the GRFPS and the merging approaches in detecting rainy and nonrainy days. Equations 3.4-3.6 present the expressions for POD , FAR , and CSI , respectively.

$$POD = \frac{H}{H+M} \quad (3.4)$$

$$FAR = \frac{F}{H+F} \quad (3.5)$$

$$CSI = \frac{H}{H+M+F} \quad (3.6)$$

where hit (H) indicates the number of daily rainfall events detected both by rainfall estimates and ground-based rainfall, miss (M) indicates the number of rainfall events not detected by rainfall estimates, and false alarm (F) indicates the number of rainfall events detected by rainfall estimates but not confirmed by ground-based rainfall. POD , FAR , and CSI ranges from 0 to 1 (inclusive) with optimal values of 1, 0, and 1, respectively.

3.2.7. Extreme Rainfall Indices

To study climate-related extreme events, more than 27 indices have been introduced by the ETCCDI (Tank et al., 2009). These indices are associated with different sectors, such as agriculture and food security, health, flood disasters, and water resources and hydrology (Baghel et al., 2022). Among these, 8 ERFIs related to heavy rainfall events, which are listed in Table 3.2, were selected and considered in this study. The indices were computed by the R-based tool “RClimDex,” which was developed by Zhang et al. (2004) using daily rainfall estimates from the RF-MERGE, CMIP5, and CMIP6 models.

For this study, ERFIs were computed at the station level and spatially averaged across the study basin to determine the average regional ERFIs. For spatial averaging, the IDW interpolation technique was employed in ArcGIS 10.4.

Table 3.2. List and descriptions of selected ERFIs

Indices	Name	Descriptions	Unit
CWD	Consecutive wet days	Annual maximum number of consecutive days when rainfall ≥ 1 mm	days
PRECTOT	Annual total wet-day rainfall	Total rainfall in wet days (> 1 mm)	mm
R20	Number of very heavy rainfall	Annual total count of days when rainfall ≥ 20 mm	days
R95p	Rainfall in very wet days	Annual total rainfall when daily rainfall > 95 th percentile	mm
R99p	Rainfall in extremely wet days	Annual total rainfall when daily rainfall > 99 th percentile	mm
RX1day	Max 1-day rainfall amount	Annual maximum 1-day rainfall	mm
RX5day	Max 5-day rainfall amount	Annual maximum consecutive 5-day rainfall	mm
SDII	Simple daily intensity index	The ratio of annual total wet-day rainfall and the number of wet days	mm/day

In Table 3.2. above, indices such as PRCPTTOT, R95p, R99p, RX1day, RX5day, and SDII can be grouped under intensity-based indices; R20 is a duration-based index, whereas CWD is a frequency-based index.

3.2.7.1. Performance evaluation of GCMs

To evaluate the performance of GCMs in simulating monthly rainfall and ERFIs, statistical performance measures are needed. These performance measures were selected from different categories. For this study, correlation, error, and bias categories of performance measures were considered. Based on this, from the error category, the root-mean-square error (*RMSE*) was selected to check the estimation accuracy of the climate model values compared to the observed values (estimates based on RF-MERGE). The Pearson correlation coefficient (*R*) was selected from the correlation category for evaluating the strength of the linear relationship between the climate model-simulated and observed values. In the bias category, PBIAS was selected for measuring the bias associated with the climate models compared with the observed values.

3.2.7.2. Normalization and weight computation for performance measures

To convert these noncommensurable statistical performance measures expressed in different spaces to a comparable space, a normalization method is recommended. In this regard, before the application normalization, the decision matrix transformation was performed, considering the most desirable and least desirable performance measures. Larger correlation values and smaller *RMSE* and PBIAS values are desirable. For this reason, a negative sign was introduced for the *RMSE* and PBIAS, whereas the

absolute value of the minimum value correlation was also added to each correlation value of the GCMs to transform the decision matrix. For this study, from several normalization methods, the sum (Type-3 method) expressed in equation 3.7 was applied (Srinivasa Raju & Nagesh Kumar, 2015).

$$X_{ij} = \frac{X_j(i)}{\sum_{i=1}^n X_j(i)} \quad (3.7)$$

where X_{ij} is the normalized value, i is the index of the GCM ($1 \leq i \leq 8$); j is the index of the performance measure ($1 \leq j \leq 3$); $X_j(i)$ is the computed value of the performance measure (j) for GCM (i); and n is the number of GCMs ($n = 8$ for both the CMIP5 and CMIP6 GCMs).

For the ranking of GCMs, weight determination for each measure is also a recommended step in addition to normalization. For this study, entropy (Pomerol & Barba-Romero, 2000; V. P. Singh, 2019), which is the most widely used objective weighting approach, was applied. Weight determination using this approach involves (1) normalization of the payoff matrix of performance measures; (2) determination of entropy for each individual performance measure; (3) determination of the degree of diversification; and (4) determination of the normalized weight of performance measures, as expressed in equations 3.8 to 3.10, respectively.

$$En_i = -\frac{1}{\ln(n)} \sum_{i=1}^n x_{ij} \ln(x_{ij}) \text{ for } j = 1, \dots, J \quad (3.8)$$

$$Dd_j = 1 - En_i \quad (3.9)$$

$$w_j = \frac{Dd_j}{\sum_{j=1}^J Dd_j} \quad (3.10)$$

where En_j is the entropy for each performance measure j ; Dd_j is the degree of diversification; w_j is the normalized weight of the performance measures; and J is the number of performance measures; for this study, $J = 3$.

3.2.7.3. GCM ranking

For this study, the technique for order preferences by similarity to an ideal solution (TOPSIS) approach was used to rank the selected GCMs based on the performance measures discussed in the previous section. TOPSIS is an M-CDM approach that is mostly applied for ranking several alternatives considering a set of criteria (Srinivasa Raju & Nagesh Kumar, 2015). This approach was proposed by Hwang & Yoon (1981) to detect the best alternative based on an ideal solution (Tzeng & Huang, 2011). In this method, the alternative that is closest to the positive ideal solution and farthest from the negative ideal solution is taken as the best alternative. Presently, the application of the TOPSIS approach is increasing because of its ability to explicitly rank GCMs (Houngue et al., 2022; Refaey et al., 2019;

Senent-Aparicio et al., 2017). To summarize, the application of the TOPSIS method involves the following six steps:

1. Normalization performance measures. The normalized performance measure $n_{kj}(x)$ for a set of alternatives (k) and the statistical performance measures (j) can be calculated as follows:

$$n_{kj}(x) = \frac{x_{kj}}{\sqrt{\sum_{k=1}^n x_{kj}^2}} \quad k = 1, \dots, n; j = 1, \dots, m. \quad (3.11)$$

2. Weighted normalized performance measure calculation, $v_{kj}(x)$:

$$v_{kj}(x) = w_j n_{kj}(x), \quad k = 1, \dots, n; j = 1, \dots, m. \quad (3.12)$$

where w_j is the weight of the j^{th} performance measure. The sum of the weights of all the performance measures is equal to 1.

3. Determination of the positive ideal solution (I^+) and negative ideal solution (I^-).

$$I^+ = \{v_1^+, \dots, v_n^+\} = \{(\max_k v_{kj}(x) | j \in b), (\min_k v_{kj}(x) | j \in b'), k = 1, \dots, n\} \quad (3.13)$$

$$I^- = \{v_1^-, \dots, v_n^-\} = \{(\min_k v_{kj}(x) | j \in b), (\max_k v_{kj}(x) | j \in b'), k = 1, \dots, n\} \quad (2.14)$$

where b and b' are associated with the benefit and cost elements, respectively.

4. Separation distance estimation from (I^+) and (I^-) using the Euclidean distance equation can be given as:

$$d_k^+ = \sqrt{\sum_{j=1}^m [v_{kj}(x) - v_j^+(x)]^2}, \quad k = 1, \dots, n \quad (3.15)$$

$$d_k^- = \sqrt{\sum_{j=1}^m [v_{kj}(x) - v_j^-(x)]^2}, \quad k = 1, \dots, n. \quad (3.16)$$

5. The relative closeness (c_k^+) from I^+ was estimated using the following equation.

$$c_k^+ = \frac{d_k^-}{d_k^+ + d_k^-}, \quad k = 1, \dots, n. \quad (3.17)$$

6. The alternatives were sorted based on the c_k^+ value from the most preferred to least preferred value.

The alternative with the highest value of c_k^+ is the most preferable, whereas the alternative with the lowest value of c_k^+ is less preferable.

For this study, the selected GCMs (CMIP5 and CMIP6 models) were taken as alternatives, and statistical performance measures (R , $RMSE$, and $PBIAS$) were used as criteria. After ranking, bias correction was performed for the four best performing models for projecting extremes under the RCP and SSP scenarios.

3.2.7.4. Bias correction

It is common that GCM simulations exhibit bias due to model assumptions, boundary conditions, resolutions, model representations, discretization, spatial averaging, and other related factors (Wang

et al., 2022; Worku et al., 2018). For this reason, it is mostly recommended that the biases of GCMs be corrected for climate change impact assessment studies (Yamamoto et al., 2021). For this study, the following four frequently used bias correction methods were selected and evaluated. Bias correction was performed to match the uncorrected model-simulated rainfall data (the best-performing CMIP5 and CMIP6 models) with the RF-MERGE data.

1. **Linear scaling (LS):** The LS method (Lenderink et al., 2007) works by considering the differences between the observed and model-simulated data to match the monthly mean of bias-corrected values with the observed values. This method adjusts the model simulated data, considering a multiplier factor for every month, as expressed in equation 3.18.

$$RF_{cor,m,d} = RF_{raw,m,d} \times \frac{\mu(RF_{obs,m})}{\mu(RF_{raw,m})} \quad (3.18)$$

where $RF_{cor,m,d}$ and $RF_{raw,m,d}$ are the corrected and model-simulated rainfall data on the d^{th} day of the m^{th} month, respectively, and $RF_{obs,m}$ and $RF_{raw,m}$ are the mean values of the observed and model-simulated rainfall data at the m^{th} month, respectively.

2. **Distribution mapping (DM):** The DM method adjusts the distribution function of the model-simulated rainfall data to match the observed distribution function by creating a transfer function (Teutschbein & Seibert, 2012). The method works based on the assumption that the observed and model-simulated data follow the same type of probability distribution function. In this method, the gamma distribution (Piani et al., 2010) expressed in equation 3.19 is assumed to be the most appropriate for describing the distributions of rainfall data.

$$f_{\gamma}(X|\alpha, \beta) = X^{\alpha-1} \frac{\exp\left(\frac{-X}{\beta}\right)}{\beta^{\alpha} \Gamma(\alpha)}; \text{ For all } X \geq 0, \alpha, \beta > 0 \quad (3.19)$$

where X is the daily model-simulated data, α and β are the shape and scale parameters of the gamma distribution, respectively, and $\Gamma(\alpha)$ is the gamma function.

3. **Quantile mapping (QM):** The QM method uses the quantile–quantile relation to match the distribution function of the model simulated to the observed one (Déqué, 2007; Enayati et al., 2021). To correct the bias of the climate model (X_{raw}), the basic point of this QM method is to use the observed value (X_{obs}) based on the following assumption:

$$F_{obs}(X_{obs}) = F_{raw}(X_{raw}) \quad (3.20)$$

which is equivalent to

$$X_{obs} = F_{obs}^{-1}[F_{raw}(X_{raw})] \quad (3.21)$$

where F_{obs} and F_{raw} represent the cumulative distribution functions (CDFs) of the observed and model-simulated rainfall data, respectively, and F_{obs}^{-1} is the inverse form of the CDF of the observed rainfall data. Among the various types of QM methods, the parametric transformation function

(PTF) was used for this study due to its wide range of applicability for studying extreme rainfall events (Soriano et al., 2019).

4. **Cumulative distribution functions-transform (CDF-t):** The CDF-t, which is a probabilistic bias correction method, was first proposed by Michelangeli et al. (2009). It is an extension of the QM method and works based on the assumption that there exists a transformation function (t) that enables the transformation of the simulated CDF into the observed CDF. This method accounts for the distribution of future climate model data, as shown in the following equation.

$$F_{obs(f)} = F_{obs(h)}(F_{raw(h)}^{-1}(F_{raw(f)}(x))) \quad (3.22)$$

where $F_{obs(h)}$ is the CDF of the observed rainfall data for the historical period, $F_{raw(h)}^{-1}$ is the inverse form of the CDF of the raw model-simulated data for the historical period, and $F_{obs(f)}$ and $F_{raw(f)}$ are the CDFs of the observed and raw model-simulated rainfall data for the future period, respectively.

3.2.7.5. Kolmogorov–Smirnov (K-S) test

The Kolmogorov–Smirnov (K-S) test is a nonparametric test for comparing the CDFs of two samples (Darling, 1957). Previous studies (Londhe et al., 2023; Tschöke et al., 2017) have shown the applicability of this test for the evaluation of bias correction methods. Therefore, the K-S test was used in this study to assess the effectiveness of the four bias correction methods. In this test, the K-S test statistic, which is the maximum deviation between the CDF of the observed $F_{obs}(x)$ and the CDF of the bias-corrected data series $F_{cor}(x)$, can be computed as follows:

$$D = \max |F_{obs}(x_j) - F_{cor}(x_j)| \text{ where } j = 1, 2, 3, \dots, n \quad (3.23)$$

The level of significance P_{value} for the K-S test at which one should not reject the hypothesis that $F_{obs}(x)$ and $F_{cor}(x)$ have equal distributions can be determined based on the algorithm provided in Nikiforov (1994).

3.2.7.6. Relative performance of the CMIP5 and CMIP6 models

For comparison and visualization of the relative performances of GCMs (CMIP5 and CMIP6 models) in reproducing ERFIs and monthly rainfall, a Taylor diagram (Taylor, 2001) was prepared. Moreover, for the quantitative evaluation of the relative performances of the CMIP5 and CMIP6 models, the Taylor skill score (Taylor, 2001) T_{SS} was computed via the following equation:

$$T_{SS} = \frac{4(1+R)}{(R_{SD}+1/R_{SD})^2(1+R_{max})} \quad (3.24)$$

where R is the spatial correlation coefficient between the observation and the model simulation, R_{SD} is the ratio of the standard deviation (SD) of the model simulation and observation, and R_{max} is the maximum attainable correlation coefficient. For this study, R_{max} was assumed to be 1 following (Chen et al., 2021).

3.2.7.7. Change analysis

The change in ERFIs was computed using the delta approach as suggested by similar recent studies (Bulti et al., 2021; Jiang et al., 2015). Using this method, the percentage change can be computed as:

$$\Delta_{ERFI} = \frac{ERFI_{future} - ERFI_{base}}{ERFI_{base}} \times 100 \quad (3.25)$$

where Δ_{ERFI} is the change in the average extreme rainfall index (%) between the baseline and the future period; $ERFI_{future}$ is the future average extreme rainfall index; and $ERFI_{base}$ is the baseline average extreme rainfall index.

3.2.7.8. Trends and variability of extreme rainfall indices

The nonparametric Mann-Kendall (M-K) (1945) trend test is the most widely applied method for characterizing the temporal trends of ERFIs (Toride et al., 2018). The test is preferred because it is less affected by outliers (Du et al., 2022) and inhomogeneity of data (Khoi et al., 2021). In addition, the M-K trend test does not require the assumption that the input data must follow a specific type of distribution. However, under some conditions, this test might be influenced by the serial autocorrelation of the input data (Tan et al., 2019). Henceforth, to remove this serial autocorrelation, the modified M-K trend test introduced by Yue et al. (2002) was applied in this study to analyze the trend of ERFIs for historical and future periods. In the modified M-K trend test, trend-free prewhitening (TF-PW) and M-K test statistics were estimated using the R package ‘modifiedmk’ (Patakamuri et al., 2020). In the M-K test, the statistic S can be computed as:

$$S = \sum_{i=1}^{N-1} \sum_{j=i+1}^N \text{Sign}(K_j - K_i) \quad (3.26)$$

where K_j and K_i are the later and earlier observations, respectively, and N is the total number of time series. Here, $\text{Sign}(K_j - K_i)$ can be given as follows:

$$\text{Sign}(K_j - K_i) = \begin{cases} 1 & \text{when } K_j - K_i > 0 \\ 0 & \text{when } K_j - K_i = 0 \\ -1 & \text{when } K_j - K_i < 0 \end{cases} \quad (3.27)$$

Using S and $\text{Var}(S)$, the Z statistic, which is the measure of the trend, can be computed using equation 3.28.

$$Z = \begin{cases} \frac{S-1}{\sqrt{\text{Var}(S)}}, & S > 0 \\ 0, & S = 0 \\ \frac{S-1}{\sqrt{\text{Var}(S)}}, & S < 0 \end{cases} \quad (3.28)$$

where Z statistics greater than zero show an increasing trend, and Z statistics less than zero show a decreasing trend. A larger absolute value of Z shows a significant trend in the time series at a certain level of significance. For this study, the significance levels of $\alpha = 5\%$ and $\alpha = 10\%$ are considered. $Z > 1.96$ and $Z < -1.96$ show significant increasing and decreasing trends, respectively, at $\alpha = 5\%$. However, $Z > 1.65$ and $Z < -1.65$ show significant increasing and decreasing trends, respectively, at $\alpha = 10\%$.

In addition, if there is a trend in the time series, its degree (slope) can be computed by Sen's estimator method, which was proposed by Sen (1968). Based on this method, the slope is given as:

$$m = \text{Median}\left(\frac{K_j - K_i}{j - i}\right), \forall j > i \quad (3.29)$$

where m is the slope of the trend, K_j and K_i are the later and earlier observations, respectively, and j and i are the order of the later and earlier observations, respectively, for all $j > i$.

The coefficient of variation (CV), which is the ratio of the standard deviation (σ) and the mean (μ), measures the degree of spatial variation at the annual scale. The larger the CV is, the larger the spatial variance, and vice versa. For this study, the following expression of CV was applied to characterize the spatial variation in each ERFI for historical and future periods.

$$CV = \frac{\sigma}{\mu} * 100 = \frac{\sqrt{\frac{1}{(N-1)} \sum_{j=1}^N (K_j - \bar{K})^2}}{\bar{K}} * 100 \quad (3.30)$$

In the above equation, CV is the coefficient of variation in (%), j is the order of the stations, K_j is the annual extreme rainfall index of the j th station, $\bar{K}$ is the average value of the ERFIs of the j th station, and N is the number of samples. According to (Hare, 2003), a CV less than 20% indicates less variability, CV between 20% and 30% indicates moderate variability, and CV greater than 30% indicates high variability (a high standard deviation relative to the average ERFI).

3.3. Results

3.3.1. Mean Rainfall Climatology Of The UBN Basin

The amount of rainfall in the UBN basin of Ethiopia was estimated based on ground-based observed rainfall stations, GRFPs, and merged estimates based on RF-MERGE. Table 3.3 summarizes the values of mean monthly and annual rainfall estimated from observed data, CHIRPS, MSWEP, ERA5-Land,

and RF-MERGE for the period 1981–2005. The results indicated that most of the rainfall estimates reproduced the distributions of observed mean monthly rainfall, despite ERA5-Land slightly overestimating rainfall, especially in rainy months (July to September). For example, the basin receives mean monthly rainfall amounts of 314.5 mm, 287.1 mm, 317.2 mm, 346.6 mm, and 300.4 mm in August, corresponding to the observed data, CHIRPS, MSWEP, ERA5-Land, and RF-MERGE, respectively (Table 3.3). This finding is consistent with the study by Alaminie et al. (2021), which confirmed ERA5-Land’s tendency to overestimate rainfall. However, compared to the individual GRFPs, the merged estimate based on RF-MERGE adequately captured rainfall amounts and patterns at different temporal scales. Similarly, previous studies (Shi et al., 2023; Vila et al., 2009; Yang et al., 2017) conducted in various basins and watersheds confirmed that merged rainfall estimates generally perform better than individual rainfall products. Overall, the estimated mean annual rainfall in the UBN basin was found to be 1331 mm (observed), 1278 mm (CHIRPS), 1416 mm (MSWEP), 1627 mm (ERA5-Land), and 1345 mm (RF-MERGE) for the period 1981–2019 (Table 3.3). Furthermore, the subsequent section provides an evaluation of rainfall estimates based on GRFPs and merged estimates in reproducing the observed mean monthly rainfall time series using statistical and categorical performance measures.

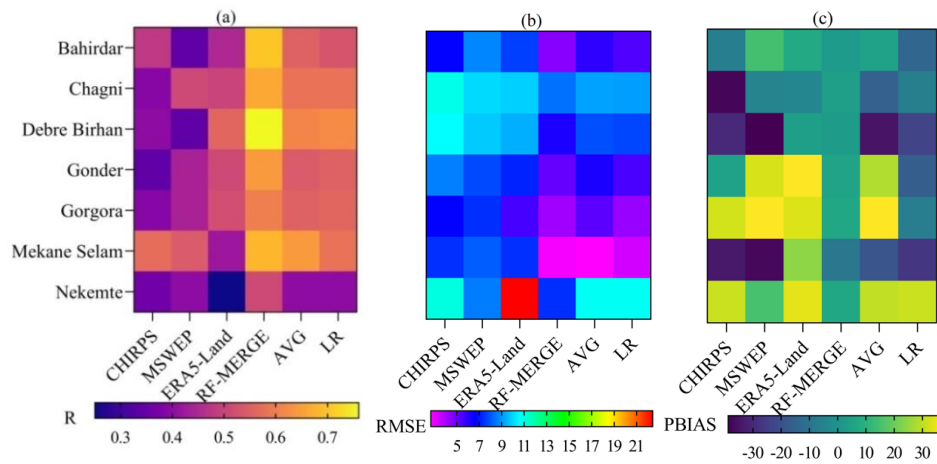
Table 3.3. Mean monthly and annual rainfall (mm) in the UBN basin 1981–2005, estimated using observed rainfall, gridded rainfall products, and the merged estimate based on RF-MERGE.

Data type	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Annual
Observed	7.9	12.8	33.2	47.9	111.9	181.6	326.5	314.3	185.9	77.6	22.2	9.3	1331
CHIRPS	6.7	11.9	32.9	52.6	124.1	183.3	293.2	287.1	181.8	79.1	18.7	7.0	1278
MSWEP	8.5	17.3	41.8	67.1	132.8	195.1	312.3	317.2	200.4	88.1	23.5	12.3	1416
ERA5-Land	7.1	15.2	45.0	70.9	157.3	242.8	336.5	346.6	262.0	111.0	26.1	6.7	1627
RF-MERGE	6.7	12.7	35.5	54.0	122.4	192.9	301.4	300.4	203.6	85.7	22.0	7.3	1345

3.3.2. Performance Evaluation of Gridded Rainfall Products and Merged Estimates

The performance of the GRFPs and rainfall estimates obtained from the merging approaches were compared on a daily scale with the ground-based rainfall using statistical and categorical performance measures. The *R*, *RMSE*, and *PBIAS* values ranged from 0.25 to 0.76, 2.68 to 22.41 mm/d, and -38.80 to 37.00%, respectively (Figure 3.2). From the results, the individual gridded rainfall products exhibit

higher values of error and bias at most of the testing stations. Among the three gridded rainfall products, ERA5-Land exhibited the worst performance, with a correlation coefficient of 0.25 and an *RMSE* of 22.41 mm/day at the Nekemte station, although it exhibited good performance at the other stations. Similarly, CHIRPS overestimated the daily rainfall (positive bias) at the Gonder, Gorgora, and Nekemte stations and underestimated it at the remaining stations. In contrast, the merged rainfall data based on RF-MERGE performed better than those based on the individual products and the two other merging approaches (AVG and LR), with higher correlation values ranging from 0.51 to 0.76 and lower *RMSE* and *PBIAS* values ranging from 2.81 to 8.17 mm/day and from -9.00 to 6.30%, respectively (Figure 3.2).



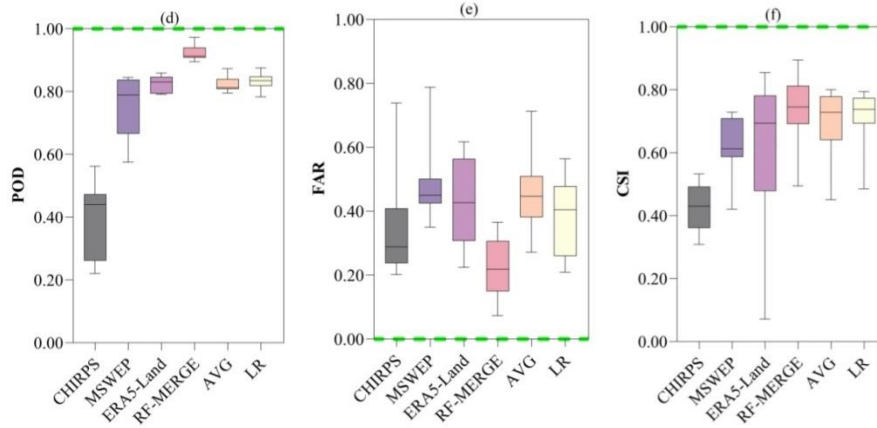


Figure 3.2. Statistical and categorical performance measures for daily rainfall data of the three gridded rainfall products and merged estimates at testing stations from 1981 to 2005. First row (a-c) shows heatmap statistical performance measures (R , $RMSE$, and $PBIAS$). Second row (d-f) shows box and whisker plots of categorical performance measures (POD , FAR , and CSI), where the green dashed lines show the optimal values of each categorical measure.

Figures 3.2 (box and whisker plots) also summarizes the performance of GRFPs and estimates based on merging approaches in terms of categorical measures. Based on the results, the three merging approaches performed better than the individual rainfall products. Overall, the RF-MERGE approach performed the best, with maximum POD and CSI values of 0.97 and 0.89, respectively. In contrast, CHIRPS, with a POD value of 0.97; MSWEP, with a FAR value of 0.78; and ERA5-Land, with a CSI value of 0.07, were found to be the least-performing GRFP products.

3.3.3. Performance of GCMs in Reproducing Extreme Rainfall Indices and Monthly Rainfall

In this study, the performances of raw GCMs (CMIP5 and CMIP6) in reproducing spatially averaged ERFIs and monthly rainfall computed based on RF-MERGE estimates (hereafter observed extremes) were evaluated separately. The heatmaps presented in Figure 3.3 show the computed statistical performance measures. From the analysis, the performance of the models was found to vary significantly for different ERFIs. For instance, in terms of R , the historical simulation of MIROC5 of CMIP5 performed best in reproducing the observed PRCPTOT ($R = 0.58$) but performed poorly in reproducing the CWD. Similarly, the historical IPSL-CM5A-LR simulation of CMIP5 performed better in reproducing the CWD ($R = 0.46$) and PRCPTOT ($R = 0.48$) but poorly in reproducing the SDII, with a correlation of -0.24. From the CMIP5 models, the lowest correlation ($R = -0.41$) was found in the CWD, which was estimated using ACCESS1-0. This shows that the CWD estimated using this model is indirectly correlated with the observed CWD. In terms of correlation, the historical MIROC5 simulations of the CMIP5 models performed better in capturing the observed short duration

index (RX5day) than did the updated version, which is the MIROC6 of the CMIP6 models, as shown in Figures 3.3a and 2-3d. Overall, most of the historical simulations of the CMIP5 and CMIP6 models performed better in reproducing the observed PRCPTOT and monthly rainfall than did the ERFIs related to heavy rainfall events.

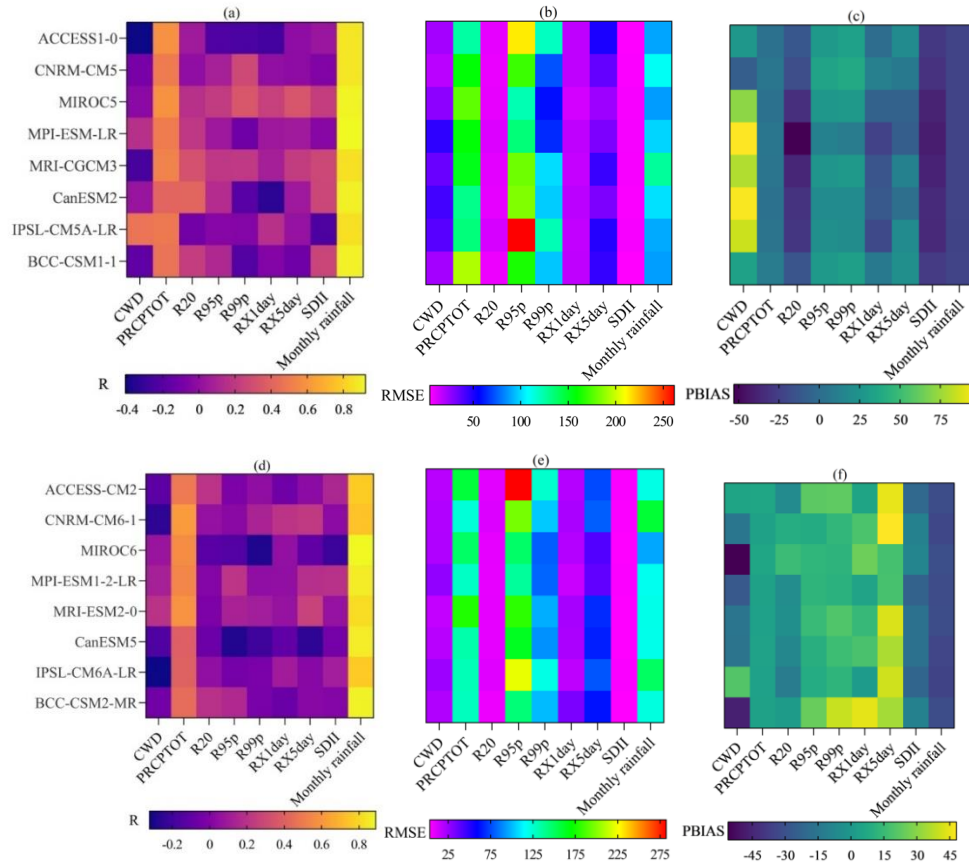


Figure 3.3. Heatmap of the statistical performance measures (R , $RMSE$, and $PBIAS$) for the CMIP5 (a-c) and CMIP6 (d-f) models in reproducing observed extreme rainfall indices and monthly rainfall (1981-2005).

In terms of $PBIAS$, some of the models overestimated (positively biased), while others underestimated (negatively biased) the observed ERFIs, as presented in Figure 3.3. From the CMIP5 models, the highest $PBIAS$ was found in the CWD simulated by MPI-ESM-LR, where the $PBIAS$ was 96.6%, followed by the CWD simulated by CanESM2 ($PBIAS=95.0\%$). Conversely, the greatest underestimation of R20 simulated by MPI-ESM-LR was also found, with a $PBIAS$ of 53.4%. For CMIP6, the greatest underestimations and overestimations were found for CWD and RX5day, which were estimated using MIROC6 ($PBIAS=56.1\%$) and CNRM-CM6-1 ($PBIAS=48.0\%$), respectively. Relative to the CMIP5 models, positive biases are dominant in the ERFIs simulated by the CMIP6 models. Considering the $RMSE$, the greatest error was found in R99p, which corresponds to ACCESS-

CM2 ($RMSE=282.1$ mm/year), followed by IPSL-CM6A-LR ($RMSE =221.3$ mm/year), as shown in Figure 3.3e.

3.3.4. Ranking Of The CMIP5 And CMIP6 Models

For this study, the performance measures presented were first normalized, and then the entropy method was applied to assign weights to each performance measure. The computed weights were used as inputs for the ranking climate models. Appendix A2 presents the weights calculated using the entropy method for the three performance measures (R , $RMSE$, and $PBIAS$). As detailed in the methods section, the TOPSIS approach was applied for the systematic ranking of GCMs based on these three predefined criteria or performance measures. Overall, considering the average ranking scores, MIROC5 of CMIP5 and MPI-ESM1-2-LR of CMIP6 acquired the highest scores as presented in Table 3.4. The findings revealed that these two models are the most skilled GCMs among the CMIP5 and CMIP6 GCMs. Similarly, Jose & Dwarakish (2022) reported better MIROC5 in simulating the RF of a tropical river basin on the southwest coast of India. On the other hand, IPSL-CM5A-LR of CMIP5 and CanESM5 of CMIP6 were the least effective models for reproducing ERFIs. However, for better representation of the local-scale climatic pattern, several studies, for example, Jose et al. (2022) and Kim et al. (2020), have recommended the use of the ensemble mean of bias-corrected best-performing (highest ranked) models. Therefore, for this study, four CMIP5 models, MIROC5, MRI-CGCM3, CanESM2, and MPI-ESM-LR, were selected, bias corrected, and ensembled (hereafter CMIP5-ensemble) for projecting ERFIs under the RCP4.5 and RCP8.5 scenarios. Similarly, from the CMIP6 models, MPI-ESM1-2-LR, MRI-ESM2-0, CNRM-CM6-1, and BCC-CSM2-MR were selected, bias corrected, and ensembled (hereafter CMIP6-ensemble) for the projection of ERFIS under the SSP2-4.5 and SSP5-8.5 scenarios.

Table 3.4. Average TOPSIS ranking scores of GCMs for reproducing ERFIs and monthly rainfall.

CMIP5			CMIP6		
GCMs	Average score	Rank	GCMs	Average score	Rank
ACCESS1-0	0.41	7	ACCESS-CM2	0.49	6
CNRM-CM5	0.51	5	CNRM-CM6-1	0.59	3
MIROC5	0.73	1	MIROC6	0.52	5
MPI-ESM-LR	0.52	4	MPI-ESM1-2-LR	0.71	1
MRI-CGCM3	0.57	2	MRI-ESM2-0	0.66	2
CanESM2	0.53	3	CanESM5	0.38	8
IPSL-CM5A-LR	0.39	8	IPSL-CM6A-LR	0.44	7
BCC-CSM1-1	0.50	6	BCC-CSM2-MR	0.56	4

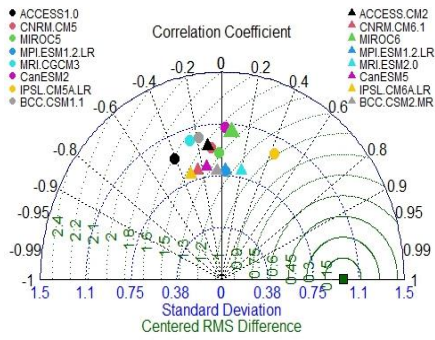
3.3.5. Comparison of the CMIP5 and CMIP6 Models

3.3.5.1. Taylor diagram

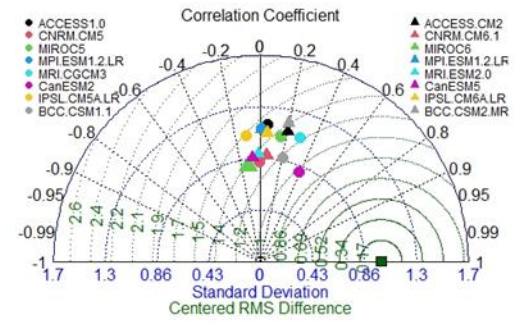
The Taylor diagram, which comprises R, centered-RMS-difference, and STDV, was used for brief summarization and comparison of CMIP5 and CMIP6 model performances in reproducing observed ERFIs and monthly rainfall. Figures 3.4 presents the Taylor diagram for the ERFIs and monthly rainfall for both the CMIP5 and CMIP6 models, where the STDV and RMS differences were normalized by the observational STDV. Based on the results, the distributions of the models in the Taylor diagram for most indices are dispersed, indicating high variability in correlation and RMS differences. In addition, the skill of the models was found to be variable for most extreme indices. For example, for CWD and PRCPTOT, the STDV values of IPSL-CM5A-LR from the CMIP5 model were found to be 0.98 and 0.95, respectively (Figures 3.4 (a-b)). However, the STDV of this model is 0.6 for monthly rainfall, indicating good model performance (Figure 3.4i).

In general, most of the model-simulated ERFIs are poorly correlated with the observed values. Similarly, Baghel et al. (2022) reported the poor performance of CMIP6 models in reproducing ERFIs in the Mekong subbasin. In their study, the authors found correlations that ranged from -0.5 to 0.35. As evidenced by several studies (Hamed et al., 2022, Kim et al., 2020), this poor correlation is attributed to the existence of high climatic variability due to the rough horizontal resolution of GCMs and bias. However, for simulating PRCPTOT and monthly rainfall, most of the models performed better, with correlations ranging from 0.38 to 0.61 and 0.74 to 0.92, respectively. From the analysis, a significant improvement in the CMIP6 ensemble in simulating monthly rainfall was also found, with a correlation of 0.94, compared to the corresponding CMIP5 ensemble, with a correlation of 0.89.

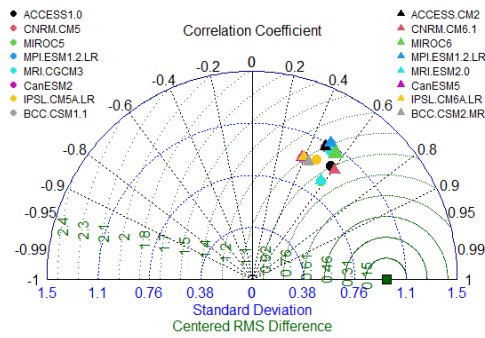
(a) CWD



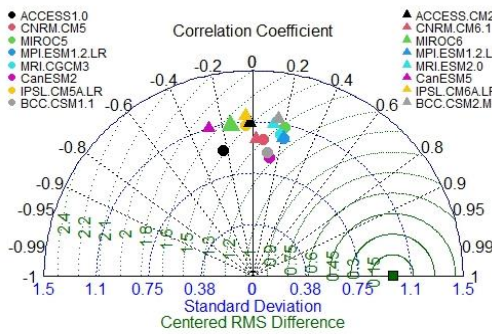
(c) R20



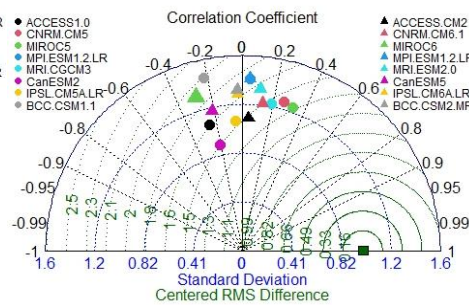
(b) PRCPTOT



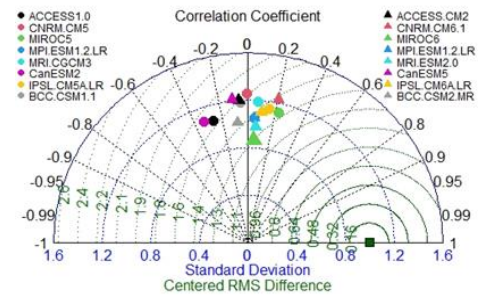
(d) R95p



(e) R99p



(f) RX1day



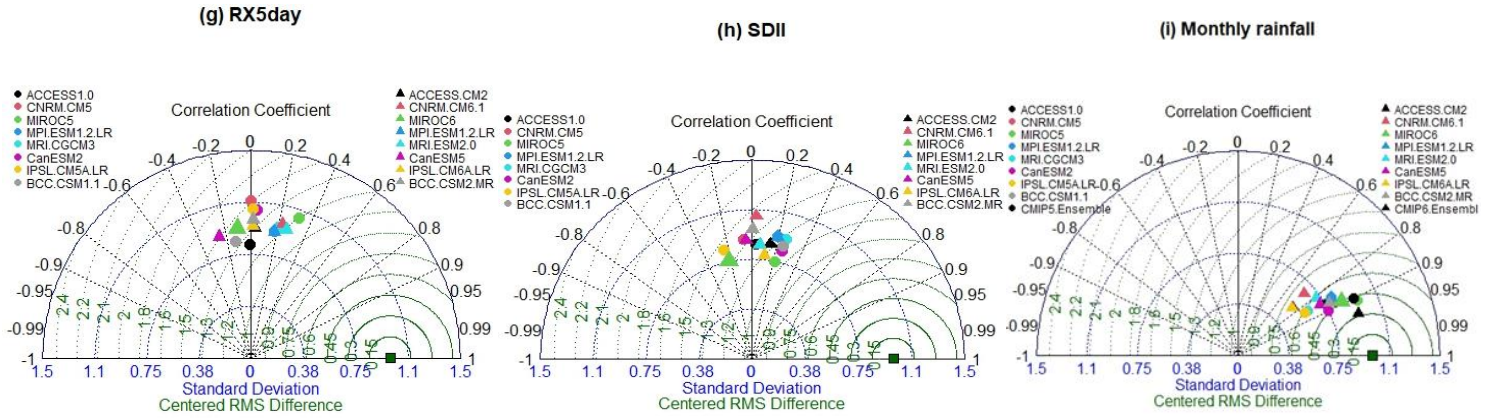


Figure 3.4. Taylor diagrams of the 8 extreme rainfall indices and monthly rainfall simulated from the 8 CMIP5 and CMIP6 models for the period from 1981 to 2005. The dots and triangles with different colours represent the CMIP5 and CMIP6 models, respectively.

3.3.5.2. Taylor skill score

The quantitative relative performances of the CMIP5 and CMIP6 models were computed by applying the Taylor skill score. Figure 3.5 (a-i) illustrates the computed skill scores for both the CMIP5 and CMIP6 models. In the figure, skill scores closer to 1 indicate better model performance in reproducing the observed ERFIs.

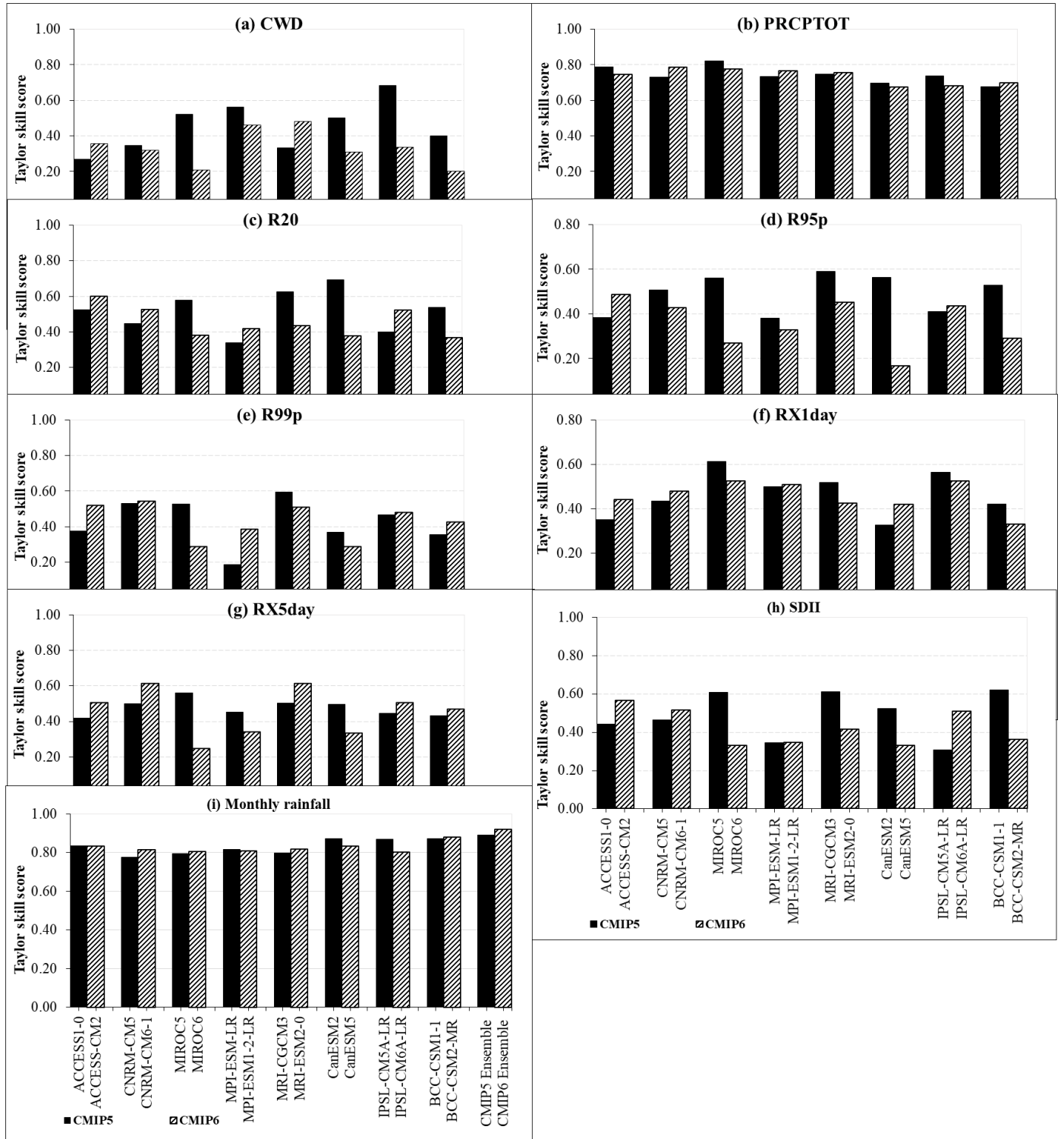


Figure 3.5. Taylor skill scores (T_{ss}) of the CMIP5 and CMIP6 climate models for the 8 ERFIs and monthly rainfall.

From the analysis, it was found that the skill scores of the models differed with the indices. For example, MIROC5 and IPSL-CM5A-LR of the CMIP5 models acquired larger scores than did the corresponding CMIP6 models for RX1day. For R95p, 6 models from CMIP5 were more skilled than

the corresponding CMIP6 models. On the other hand, the numbers of CMIP6 models that performed better in reproducing the observed ERFIs, such as R20, RX1day, and RX5day, were 4, 4, and 5, respectively, as shown in Figures 3.5 (c, f, g). As an example, ACCESS-CM2, CNRM-CM6-1, MPI-ESM1-2-LR, and IPSL-CM6A-LR are among the CMIP6 models that were found to be skilled relative to the CMIP5 models in reproducing the observed R20, with scores of 0.60, 0.52, 0.42, and 0.52, respectively (Figure 3.5c). For monthly rainfall, the CMIP6 ensemble performed better than the individual models and the corresponding CMIP5 ensembles, with an approximate skill score of 0.94. This indicates the importance of the CMIP6-Ensemble over the CMIP5-Ensemble in simulating the monthly rainfall in the UBN basin, which is similar to the findings of other previous studies (Kamruzzaman et al., 2021; Lin & Chen, 2020; Wang et al., 2022).

3.3.6. Evaluation of Bias Correction Methods

Four bias correction methods were used to correct the bias of the model-simulated rainfall data. To evaluate the performance of the bias correction methods, the K-S statistical test was employed. In this test, high values of K-S statistics D show inequality in CDFs, while low values show equality (similarity) in CDFs. Table 3.5 presents the results of the K-S statistics D and p_{value} and before and after the application of bias correction methods for the mean monthly rainfall. According to the results, most of the bias correction methods reduced the K-S test statistic D . For instance, the LS, DS, QM, and CDF-t methods reduced the D value of uncorrected BCC-CSM2-MR from 0.133 to 0.086, 0.077, 0.080, and 0.068, respectively (Table 3.5). This indicates better performance of the bias correction methods in improving the quality of the model simulated data. This model also showed an increase in p_{value} from 2.354% to 24.8, 34.5, 29.36, and 53.09% after the application of the corresponding bias correction methods.

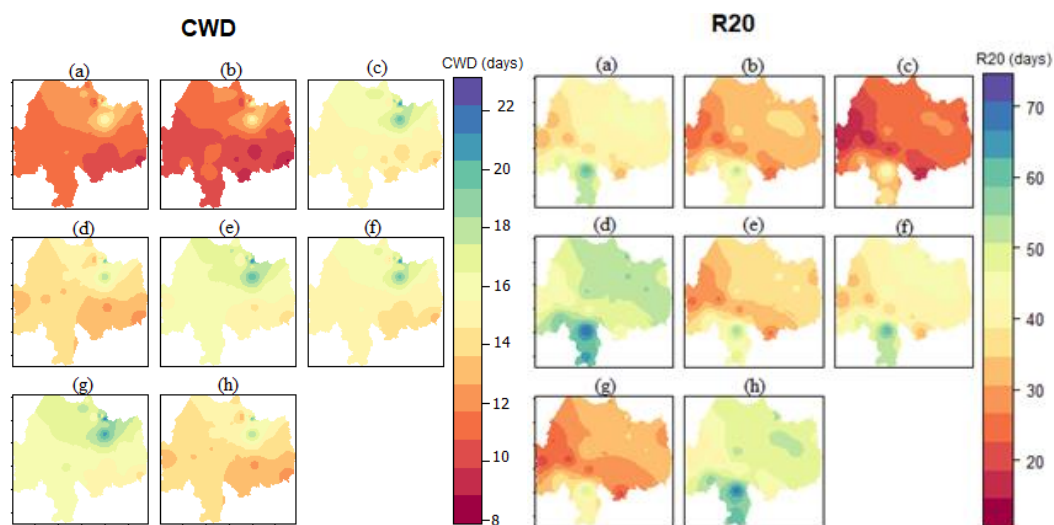
In contrast, the LS and DM methods were not found to be efficient at reducing bias for some models. For instance, LS bias correction was not found to be as efficient as other methods in reducing the D values of uncorrected MPI-ESM-LR, MPI-ESM1-2-LR, MRI-ESM2-0, and CNRM-CM6-1. Similarly, the DM method performed poorly in reducing the D value for the MPI-ESM1-2-LR and CNRM-CM6-1 models. In general, for this study, the QM method achieved the first rank in reducing bias for the six models in terms of D . In addition to QM, CDF-t was found to be an efficient method for acquiring the first rank for the two models (MRI-ESM2-0 and BCC-CSM2-MR) (Table 3.5). To be consistent, the QM method was selected for this study for correcting bias in the climate models, as it performed effectively in reducing bias for most of the models. Similar to these findings, previous studies (N. Acharya et al., 2013; Soriano et al., 2019) reported better performance of the QM method.

Table 3.5. K-S test statistics for the cumulative distribution functions (CDFs) of the model simulated (uncorrected) and bias-corrected mean monthly rainfall based on the LS, DM, QM, and CDF-t methods.

GCMs	No correction		LS		DM		QM		CDF-T	
	D	p_{value} (%)	D	p_{value} (%)	D	p_{value} (%)	D	p_{value} (%)	D	p_{value} (%)
MIROC5	0.130	0.016	0.099	11.680	0.123	2.353	0.073	60.100	0.130	1.818
MRI-CGCM3	0.268	0.226	0.127	1.818	0.152	0.242	0.082	29.360	0.132	1.394
CanESM2	0.095	14.260	0.078	34.490	0.051	81.060	0.050	87.060	0.088	20.770
MPI-ESM-LR	0.189	0.727	0.258	0.116	0.152	0.243	0.106	7.667	0.141	0.802
MPI-ESM1-2-LR	0.120	2.354	0.258	0.016	0.152	5.870	0.106	2.354	0.140	11.680
MRI-ESM2-0	0.124	2.354	0.183	0.016	0.109	5.870	0.123	2.354	0.098	11.680
CNRM-CM6-1	0.120	3.025	0.138	0.802	0.132	1.394	0.084	24.800	0.108	1.818
BCC-CSM2-MR	0.133	2.354	0.086	24.800	0.077	34.500	0.080	29.360	0.068	53.090

3.3.7. Spatial Distribution of Extreme Rainfall Indices

Figure 3.6 illustrates the spatial distribution of both observed and projected ERFIs namely: CWD, R20, PRCPTOT, RX1day, RX5day, and R99p interpolated using the IDW technique. The historical ERFIs were derived from RF-MERGE rainfall data, while the projected ERFIs were based on CMIP5 and CMIP6 multi-model ensembles. The rainfall distribution maps indicate that most ERFIs exhibit similar spatial patterns across both historical and future periods, with the highest values predominantly concentrated in the southern parts of the basin. For example, maximum PRCPTOT values reach up to 2200 mm, and RX1day values peak at approximately 80 mm in the southern region of the basin.



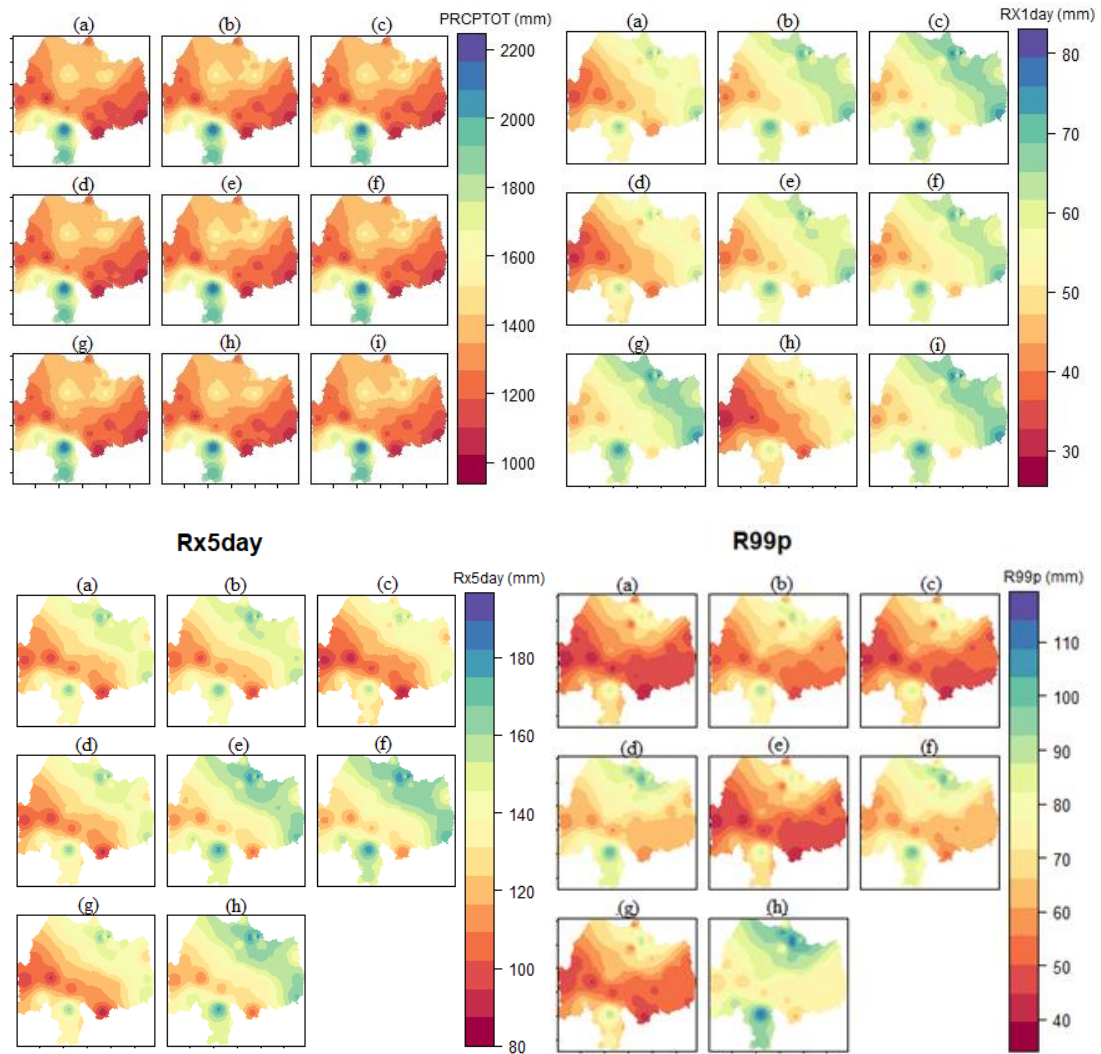


Figure 3.6. Spatial distributions of the observed and projected ERFIs. (a) Long term observed (1981–2019), (b) RCP4.5 (2031–2055), (c) RCP4.5 (2056–2080), (d) RCP8.5 (2031–2055), (e) RCP8.5 (2056–2080), (f) SSP2-4.5 (2031-2055), (g) SSP2-4.5 (2056-2080), (h) SSP5-8.5 (2031-2055), (i) SSP5-8.5 (2056-2080).

3.3.8. Changes in Extreme Rainfall Indices

Using the historical ERFIs (1981–2005) as a baseline, projected changes in ERFIs for future periods were computed, as presented in Appendix A3. Consistent with the IPCC’s 5th Assessment Report (2014), most of the ERFIs in the UBN basin are likely to increase in the future. Comparatively, negative values or reductions in some intensity-based indices, such as R95p, R99p, and SDII, were found under RCP8.5 and SSP5-8.5 for this period (2031-2060). Considering all the change results, consistent increases in CWD and RX5day were found in all periods and scenarios. From the analysis, the maximum decrease in R95p (-15.08%) was found under RCP8.5 (2031-2060), while the maximum Increase In CWD (27.5%) Was Found Under SSP5-8.5 (2031-2055) (Appendix A3).

3.3.9. Trends, Variability, and Correlation of Extreme Rainfall Indices

Based on the M-K Z-statistics, all of the ERFIs showed a positive or increasing trend except for R99p. R20 showed a significant positive trend ($Z = 1.88$) at the 10% significance level, with a slope of 0.83 mm/decade as shown in Table 3.6. In contrast, R99p showed an insignificant negative trend ($Z = -1.08$) with a slope of -0.25 mm/year. From the results, it is clear that the direction of the trend of the observed ERFIs varies from index to index. Similar to these findings, previous studies reported both increasing and decreasing trends for different types of ERFIs. For instance, Mekasha et al. (2013) reported an increasing trend of RX1day and R99p in the highlands of Ethiopia but a significant decreasing trend for RX5day in the eastern part of Ethiopia. Worku et al. (2018) found both increasing and decreasing trends of PRCPTOT, R95p, and R95p at different observation stations in the Jemma subbasin for the period of 1981–2018. Similarly, Likinaw et al. (2023) investigated the variation in the trends of ERFIs in the Northwest Ethiopia for the period of 1981–2018. In this regard, the authors found increasing trends of CWD, PRCPTOT, SDII, and R95p and decreasing trends of RX1day and R99p. As stated in previous studies (Berhane et al., 2020; Gummadi et al., 2018), this inconsistent trend of different types of ERFIs in different parts of Ethiopia is due to the strong associations among elevation, agroclimatic zones, and the spatial variability of extremes. Details on the graphical plot of the long-term linear trend of observed ERFIs across the study basin from 1981 to 2019 are available in 2.8. Furthermore, the M-K trend Z statistics and the slopes of projected ERFIs based on the multi-model ensemble are provided in Appendix A4.

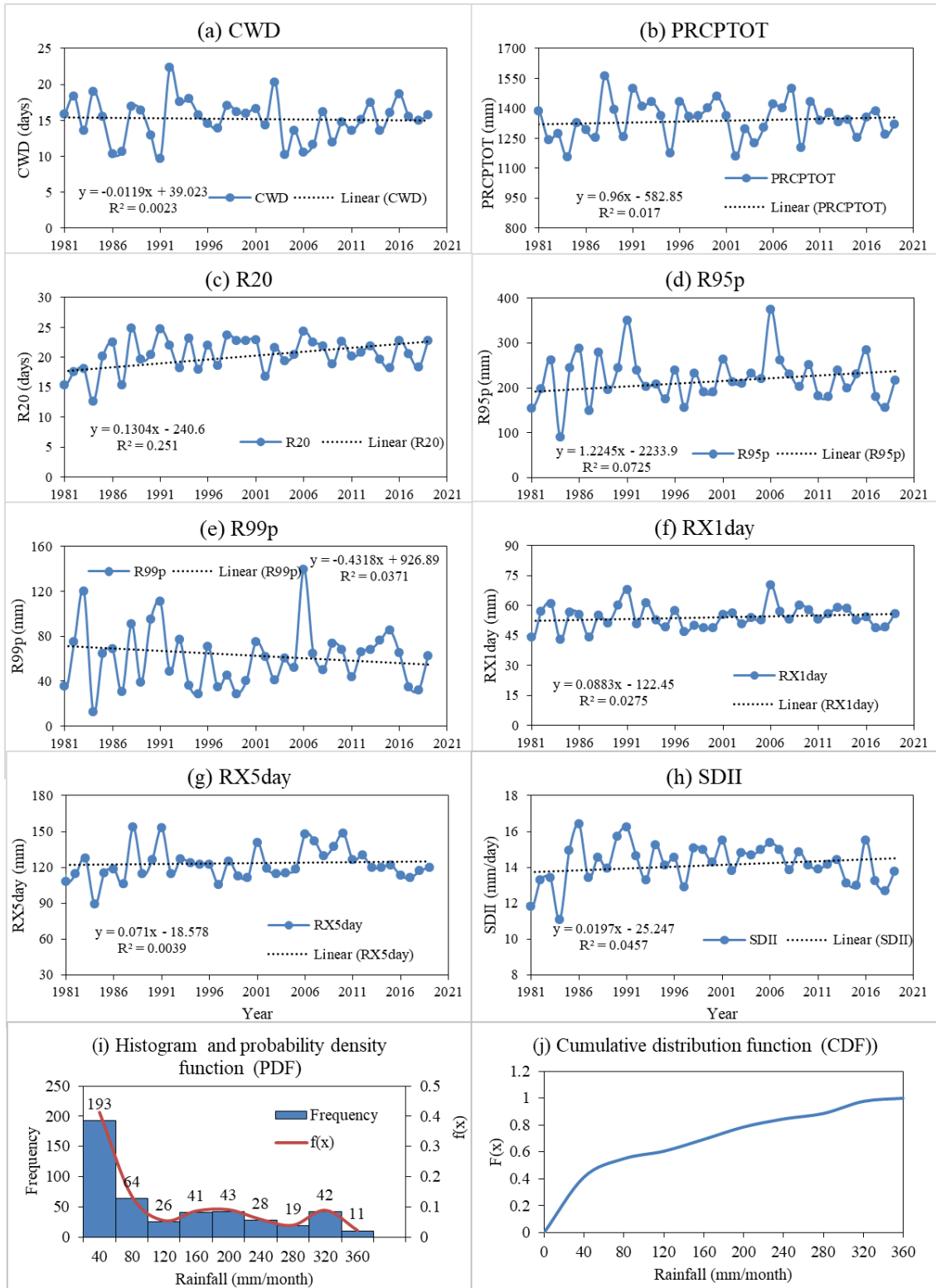


Figure 3.7. (a) to (h) Long-term temporal variation in the 8 extreme rainfall indices, (i) histogram and probability density function (pdf) of the monthly rainfall series, and (j) cumulative distribution function (CDF) of the monthly rainfall series over the UBN basin (1981–2019). The black dashed line shows the linear trend line of each extreme rainfall index.

Table 3.6. Mann-Kendall (M-K) trend Z statistics, P-value, slope, and coefficient of variation of extreme rainfall indices (ERFIs) for the observation period from 1981 to 2019.

ERFI	Z	P-value	Slope	CV (%)
CWD	0.25	0.772	0.02	43.35
PRCPTOT	0.41	0.429	10.95	12.41
R20	↑1.88	0.001	0.83	29.12
R95p	1.25	0.097	10.69	58.08
R99p	-1.08	0.240	-2.50	63.30
RX1day	1.28	0.313	1.25	26.60
RX5day	0.55	0.705	0.80	21.43
SDII	0.21	0.194	0.00	15.40
Monthly rainfall	0.25	0.189	0.04	10.14

In the table above, ↑ indicates a significant positive trend (P-value less than 0.01) at $\alpha = 10\%$. The units of slope for each index are CWD (days/decade), PRCPTOT (mm/decade), R20 (days/decade), R95p (mm/decade), R99p (mm/decade), RX1day (mm/decade), RX5day (mm/decade), and SDII (mm/day/decade).

The CV of the observed ERFIs for the period 1981 to 2019 was computed at each station and interpolated over the study basin. Table 3.6 (column 4) shows the mean values of CV for each observed ERFI. Based on the results, indices such as CWD, R95p, and R99p were found to be highly variable, with CVs greater than 30%. Similar to this, previous studies Abtew et al. (2009) and Ayehu et al. (2021) reported high variability rainfall in the basin. The remaining indices, such as RX1day, RX5day, and R20, were found to be moderately variable, with coefficients of variation (CVs) between 20% and 30%. In contrast, PRCPTOT, SDII, and the monthly rainfall series were less variable, with CV values below 20%. Additionally, the CVs of the projected ERFIs are provided in Appendix A5.

In addition to the trends and viability of ERFIs described above, a linear relationship correlation exists between each ERFI computed and presented in Table 3.7. For this, the critical correlation coefficient was found to be ± 0.3125 at a significance level of 5%. Based on this critical value, most of the extreme rainfall indices exhibited a statistically significant positive correlation. From these, a very strong statistically significant correlation was found between RX1day and R99p ($R = 0.8981$). In contrast, CWD, which is frequency-based ERFI, showed a negative correlation with all of the ERFIs except for PRCPTOT, where it showed a statistically nonsignificant positive correlation ($R = 0.0831$). From these, a strong negative correlation was found between R99p and CWD ($R = -0.3834$).

Table 3.7. Correlations (R) between extreme rainfall indices for the study basin during the observation period (1981–2019).

Indices	CWD	PRCPTOT	R20	R95p	R99p	RX1day	RX5day	SDII
CWD	1							
PRCPTOT	0.0831	1						
R20	-0.0299	0.6845	1					
R95p	-0.3138	0.4162	0.7244	1				
R99p	-0.3834	0.2097	0.3717	0.8097	1			
RX1day	-0.3806	0.2139	0.4573	0.7876	0.8981	1		
RX5day	-0.3422	0.4752	0.6178	0.7216	0.6906	0.7293	1	
SDII	-0.2586	0.2607	0.7709	0.7428	0.3992	0.5146	0.5154	1

In the above table, the correlation values shown in bold are non-significant at $\alpha = 5\%$.

3.4. Discussion

3.4.1. Observed Extreme Rainfall Indices

The observed ERFIs were computed based on daily rainfall estimates from RF-MERGE, which combines ground-based rainfall with GRFPs (CHIRPS, MSWEP, and ERA5-Land). RF-MERGE was applied to improve the quality of rainfall data by overcoming the effect of the sparse distribution of ground-based stations and topography on rainfall estimation (Belay et al., 2022). To guarantee the performance of RF-MERGE in improving the quality of rainfall estimates, it was compared with conventional merging approaches (AVG and LR) based on point-pixel evaluation using statistical and categorical performance measures. Based on the results, rainfall estimates based on the RF-MERGE approach performed better than those based on the individual GRFPs and the two merging methods. Consistent with this study, recent studies reported better performance of RF-MERGE in improving the quality of rainfall data (Nguyen et al., 2021; Shi et al., 2023). In this regard, the improved input data can be used not only for the computation of ERFIs but also as an input to hydrological models for studying the water resources of the study basin (Lakew et al., 2020; Mekonnen et al., 2022).

3.4.2. Performance Evaluation of the GCMS in Reproducing Extreme Rainfall Indices

Before the computation of ERFIs, the NASA dataset used in this study was initially assessed using different downscaling approaches. From the results, the NASA datasets showed better performance in reproducing the monthly rainfall pattern of the study basin, which is similar to previous studies (Jose & Dwarakish, 2022; Sharma & Kale, 2022). Following the initial assessment, statistical performance measures such as R , RMSE, and PBIAS were considered for evaluating the performances of the NASA CMIP5 and CMIP6 models in reproducing ERFIs. From the analysis, it was found that the performance of the models varies across different indices. For instance, a model that performed best in reproducing

RX1day and RX5day in terms of correlation may perform poorly in reproducing CWD or any other indices in terms of PBIAS. Similar to these findings, recent studies have indicated the index-dependent skill of the CMIP5 and CMIP6 models (Chen et al., 2021; Sharma & Kale, 2022; Wang et al., 2021). To handle such discrepancies, normalization of performance measures was employed for ranking climate models based on their TOPSIS ranking skill score. Overall, the ensemble means of the top-ranked CMIP5 and CMIP6 models outperform in capturing rainfall patterns, which is consistent with recent studies conducted in Bangladesh (Kamruzzaman et al., 2021), the southwestern coast of India (Jose & Dwarakish, 2022), and East Africa (Almazroui et al., 2020). Based on this, top-ranked models were selected and bias-corrected, and their ensemble means were used for projecting future extremes under the RCP and SSP scenarios. In this regard, to obtain a good approximation of the local climate, downscaled GCM data need to be bias-corrected using observed data. As stated in several studies, there is no single bias correction method that performs best for all regions due to the variation in the spatiotemporal characteristics of rainfall (Beyer et al., 2019; Kaur & Kaur, 2023). For this reason, it is recommended that different bias correction methods be used. In this study, four bias correction methods were evaluated, and the best-performing method was selected to correct the bias of the climate models.

In this study, ERFIs such as CWD and RX5day consistently increased under the RCP and SSP scenarios. The remaining indices showed inconsistent changes (both positive and negative changes) under the different scenarios. In the UBN basin, several climate change studies have reported variable changes in rainfall (Alaminie et al., 2021; Cherie, 2013). Some studies reported positive, or increasing, changes, while others reported negative, or decreasing, changes. The factors attributed to this variation include the existence of high rainfall variability, a lack of high-quality ground-based rainfall data, differences in the selection of bias correction by different researchers, differences in the selection of climate models, and the coarse spatial resolution of the GCMs (Elshamy et al., 2009). Furthermore, in the UBN basin, several studies have evaluated the performance of climate models for studying climate change impacts on water availability (Haile et al., 2017; Mengistu et al., 2021; Wagena et al., 2016). However, less consideration has been given to the impact of climate change on extreme hydrological events. Hence, this study can provide input for the selection of high-resolution climate models for studying climate change impacts on hydrological extremes.

3.4.3. Variability and Trends of Extreme Rainfall Indices

In the study basin, most of the computed ERFIs (for example, R95p, R99p, and CWD) exhibited high variability, which is similar to the findings of previous studies (Bewket & Conway, 2007; Dawit et al., 2019; Mohammed et al., 2019). For example, Addisu et al.(2015) reported high variability in rainfall

ranging from 20 to 89% in the Lake Tana subbasin. Other researchers reported high variability in rainfall in the study basin (Abtew et al., 2009; Ayehu et al., 2021). This high variability in ERFIs indicates the vulnerability of the basin to climate-related extreme events (Mohammed et al., 2019; Worku et al., 2019). Furthermore, most of the computed ERFIs showed a statistically insignificant increasing trend for both the observation and future periods. In this regard, several previous studies reported different trend magnitudes with varying directions (Addisu et al., 2015; Alemayehu et al., 2020; Ali Mohammed et al., 2022). Some of the factors attributed to these differences include subjective partitioning of the study area by different researchers, the type of rainfall data used (satellite or gauge rainfall), differences in the duration of the study period, differences in the quality of rainfall data, and the sparse distribution of rainfall stations (Mohammed et al., 2019; Seleshi & Zanke, 2004). In addition, rainfall characteristics in Ethiopia are nonuniform and highly correlated with topography and other biophysical factors (Haile et al., 2009). Overall, the results of this study suggest the need for developing and implementing climate change adaptation and mitigation strategies to reduce the adverse effects of climate change on extreme events and water resources.

3.5. Conclusions

In this study, the performances of 16 GCMs (8 CMIP5 and 8 CMIP6) were compared and evaluated for reproducing observed ERFIs and monthly rainfall in the UBN basin of Ethiopia. The observed ERFIs were computed based on RF-MERGE estimates, which combine ground-based observed rainfall with GRFPs. For the evaluation, three statistical performance measures (R, RMSE, and PBIAS) were used for the historical period of 1981–2005, and then TOPSIS, which is the M-CDA approach, was employed to rank the GCMs based on their performance. Afterwards, the four most skilled CMIP5 models were selected for bias correction and ensemble prediction for projecting ERFIs under the RCP4.5 and RCP8.5 scenarios for the two future periods of 2031–2055 and 2056–2080. Similarly, the four most skilled CMIP6 models were selected for bias correction and ensemble prediction for projecting ERFIs for the same future periods under the SSP2-4.5 and SSP5-8.5 scenarios. Consequently, the percentage changes, variability, and trends of ERFIs were analyzed for both historical and future periods. In addition, the relative performances of the CMIP5 and CMIP6 models were also evaluated. Therefore, the findings of the study are summarized as follows:

- Based on the average TOPSIS ranking score, MIROC5, MRI-CGCM3, CanESM2, and MPI-ESM-LR of CMIP5 and MPI-ESM1-2-LR, MRI-ESM2-0, CNRM-CM6-1, and BCC-CSM2-MR of CMIP6 were found to be the most suitable models for capturing ERFIs and monthly rainfall.

- Positive changes were found for CWD and RX5day under RCP8.5 and SSP5-8.5 relative to the baseline period, whereas the remaining indices showed inconsistent changes under different scenarios.
- CWD, R95p, and R99p were highly variable; R20, RX1day, and RX5day were moderately variable; and the rest of the indices (PRCPTO and SDII) were less variable for the observation period.
- Based on the M-K trend test results, most of the ERFIs showed inconsistent trends for both the observation and future periods.

Finally, the results of this study provide information on the frequency, intensity, and duration of extreme rainfall events, along with their spatiotemporal variations and trends for historical and future periods. The results of this study can be expanded by assessing the impacts of extreme rainfall events on hydrological extremes and water resources to provide information for decision-making and to identify proper climate change adaptation and mitigation measures. In this study, the IDW interpolation technique was applied to represent the spatial distribution of ERFIs. For this interpolation technique, geographic proximity, or the distance between stations, is the main parameter. However, future studies can apply other interpolation techniques, such as geographically weighted regression and kriging, and compare the results with those of the IDW technique. Additionally, in this study, the performance evaluation of the models was based on a past performance approach, which is based on the performance of climate models in reproducing observed ERFIs and monthly rainfall. However, there are also other approaches (e.g., envelope and advanced envelope approaches) that consider the uncertainty of future projections of climate models. Hence, future studies can compare these model selection and evaluation approaches with the past performance approach that was applied in this study.

CHAPTER 4

4. Scenario-Based Land Use and Land Cover Change Detection and Prediction Using the Cellular Automata–Markov Model in the Gumara Watershed, Upper Blue Nile Basin, Ethiopia

This chapter has been published as:

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Abstract

Land use and land cover (LULC) change detection and prediction studies are crucial for supporting sustainable watershed planning and management. Hence, this study aimed to detect historical LULC changes from 1985 to 2019 and predict future changes for 2035 (near future) and 2065 (far future) in the Gumara watershed, Upper Blue Nile (UBN) Basin, Ethiopia. LULC classification for the years 1985, 2000, 2010, and 2019 was performed using Landsat images along with vegetation indices and topographic factors. The random forest (RF) machine learning algorithm built into the cloud-based platform Google Earth Engine (GEE) was used for classification. The results of the classification accuracy assessment indicated perfect agreement between the classified maps and the validation dataset, with kappa coefficients (K) of 0.92, 0.94, 0.90, and 0.88 for the LULC maps of 1985, 2000, 2010, and 2019, respectively. Based on the classified maps, cultivated land and settlement increased from 58.60 to 83.08% and 0.06 to 0.18%, respectively, from 1985 to 2019 at the expense of decreasing forest, shrubland and grassland. Future LULC prediction was performed using the cellular automata–Markov (CA–Markov) model under (1) the business-as-usual (BAU) scenario, which is based on the current trend of socioeconomic development, and (2) the governance (GOV) scenario, which is based on the Green Legacy Initiative (GLI) program of Ethiopia. Under the BAU scenario, significant expansions of cultivated land and settlement were predicted from 83.08 to 89.01% and 0.18 to 0.83%, respectively, from 2019 to 2065. Conversely, under the GOV scenario, the increase in forest area was predicted to increase from 2.59% (2019) to 4.71% (2065). For this reason, this study recommends following the GOV scenario to prevent flooding and soil degradation in the Gumara watershed. Finally, the results of this study provide information for government policymakers, land use planners, and watershed managers to develop sustainable land use management plans and policies.

Keywords: land use and land cover prediction; change detection; Google Earth Engine; random forest; CA–Markov; scenario-based prediction

4.1. Introduction

Recently, land use and land cover (LULC) change detection and prediction have become popular research topics in the area of remote sensing; thus, these issues have attracted the attention of several researchers and land use planners (Navin & Agilandeewari, 2020; Tadese et al., 2021). This is due to the significant effect of LULC changes on altering the hydrological characteristics of basins and watersheds, climate change (Otukey & Blaschke, 2010), and other environmental issues (Thanh Noi & Kappas, 2017). Globally, different LULC classes of basins and watersheds have undergone considerable changes from one category to another due to increasing anthropogenic activities such as deforestation, agricultural expansion, urbanization, mining, and other related activities (Abijith & Saravanan, 2021; Arfasa et al., 2023; Chang et al., 2021). For this reason, regularly updating LULC maps is an important task for capturing the dynamic nature of land use (Shafizadeh-Moghadam et al., 2021).

For spatiotemporal LULC mapping, remotely sensed multispectral images available at various spatiotemporal resolutions provide vital information. Some of these images include Moderate Resolution Imaging Spectroradiometer (MODIS), Satellite Pour l'Observation de la Terre (SPOT), Synthetic Aperture Radar (SAR), Landsat series, Sentinel-2 missions, and Rapid Eye Earth Imaging System (REIS) images (Navin & Agilandeewari, 2020). From these images, the Landsat series has been used in a number of LULC mapping studies (Noi Phan et al., 2020; Otukey & Blaschke, 2010).

In LULC classification studies, the use of cloud-free composites of time-series images is more strongly recommended than the use of single images (Shafizadeh-Moghadam et al., 2021; Xiong et al., 2017). However, the traditional methods of searching, filtering, cloud masking, compositing, downloading, and classifying time series images require high computing power and a large volume of data storage. For this purpose, Google Earth Engine (GEE), which is a cloud-based platform, can solve the problems associated with big data processing (Abijith & Saravanan, 2021; Stromann et al., 2020). This platform has recently been considered a powerful tool for processing and analyzing large volumes of remote sensing data. In the GEE environment, there are various supervised machine learning (SML) classification algorithms. Some of these include decision tree (DT), random forest (RF), naive Bayes (NB), minimum distance (MD), and classification and regression tree (CART) methods (Camargo et al., 2019; Neetu & Ray, 2019; Thanh Noi & Kappas, 2017). In this regard, several studies comparing SML classifiers have recommended the RF algorithm because it has the highest classification accuracy and the potential to handle high-dimensional data with a minimum number of parameters (Adam et al., 2014; Breiman, 2001; Tassi & Vizzari, 2020). Moreover, the use of topographic factors and spectral indices can improve classification accuracy (Kadri et al., 2023).

In addition to the LULC classification discussed above, LULC prediction is important for simulating future landscape conditions and determining the potential driving factors that cause land use change. According to the comprehensive review of Navin & Agilandeeswari (2020), there are various temporal prediction models (for example, the Markov chain and system dynamics (SD)) and spatial prediction models (for example, cellular automata (CA) and conversion of land use and its effects (CLUE)) and hybrids of the two model categories. Recently, LULC prediction using hybrid models, such as the cellular automata–Markov (CA–Markov) model, has become an effective approach because it integrates both spatial and temporal simulation powers of the CA and Markov models. For this reason, a number of researchers have applied the CA–Markov model for predicting future LULC dynamics at the basin, watershed, and even city levels (Hamad et al., 2018; Leta et al., 2021b; Sisay et al., 2023).

The prediction of future LULC dynamics based on historical trends is a critical issue (Halmy et al., 2015). However, the assumption of the continuity of the current land use trend is mostly susceptible to uncertainties due to the dynamic nature of land use change driver variables (Ruben et al., 2020; Shoyama, 2021). For this purpose, scenario-based LULC change analysis is mostly recommended as a tool to explore such uncertainties (Van Vuuren et al., 2012). Recently, five shared socioeconomic pathways have been proposed for possible future socioeconomic development, climate change, and land use policies (O'Neill et al., 2017; Popp et al., 2017). These SSP-based pathways provide information for research and policies related to land use and climate change to reduce the adverse impacts of rapid population growth, intensive agricultural cultivation, and greenhouse gas emissions (Popp et al., 2017). Therefore, several scenario-based LULC change analysis studies have also been conducted at different spatiotemporal scales. For example, Wang et al. (2018) employed the CA–Markov model for simulating future LULC under environmental protection (EPS), crop protection (CP), and spontaneous (SP) scenarios in Tianjin city. The authors found a dramatic increase in built-up areas under the SP scenario relative to those under the EP and CP scenarios. Similarly, Gebresellase et al. (2023) simulated future LULC dynamics in the Upper Awash Basin of Ethiopia using the CA–Markov model for the years 2030 and 2060 under the BAU and governance (GOV) scenarios, considering various spatial driving variables. The authors found a significant increase in cultivated land and settlement under the BAU scenario and an increase in forest area under the GOV scenario.

In Ethiopia, several studies have been conducted on historical LULC change detection at the basin and watershed scales (Berihun et al., 2019a; Chakilu & Moges, 2017; Yesuph & Dagne, 2019). These historical LULC change detection studies are vital for better understanding the interactions between human activities and their surroundings (Dibaba et al., 2020; Tolessa et al., 2020). In addition to historical LULC change detection, information on future LULC change trends over a long period of

time is also critical. As LULC change rapidly varies in Ethiopia due to human and natural factors (Bogale, 2020), modeling and documenting future LULC dynamics is important for providing information for land use planners and policymakers to develop sustainable land use management plans (Faichia et al., 2020). However, in Ethiopia, less attention has been given to the prediction of future LULC dynamics, except for a few recent studies conducted in the Omo-Gibe River Basin (Lukas et al., 2023), Upper Awash River Basin (Gebresellase et al., 2023), Nashe watershed (Leta et al., 2021b), Goang watershed (Sisay et al., 2023), Majang Forest Biosphere Reserve (Tadese et al., 2021), and Addis Ababa and surrounding areas (Mohamed & Worku, 2020).

The Gumara watershed is a subwatershed of the Lake Tana subbasin in the Upper Blue Nile Basin (UBNB) of Ethiopia. Previous studies conducted in watersheds frequently used the maximum likelihood (ML) algorithm for LULC classification (Anteneh & Mohammed, 2020; Wubie et al., 2016), which requires normally distributed data for classification (Szuster et al., 2011). However, less consideration has been given to robust machine learning classifiers such as the RF algorithm, which does not require the assumption that the data need to be normally distributed. The Gumara watershed was selected as the study area since it is highly prone to soil erosion in the uplands and flooding in the lowlands resulting from LULC change (Bogale, 2020; Desta et al., 2019). For these reasons, the present study aims (1) to map the historical LULC dynamics using the RF algorithm built into the GEE environment for the years 1985, 2000, 2010, and 2019; (2) to detect LULC changes in the historical period (1985–2019); and (3) to predict future LULC dynamics under the BAU and GOV for the years 2035 and 2065 using the CA–Markov model, which is available from the IDRISI Selva17.0 software package. In this regard, the BAU scenario is based on the current trends of socioeconomic development, urbanization, intensive crop production, rapid population growth, the development of large industrial parks, and the construction of infrastructure (Mohamed & Worku, 2020). On the other hand, the GOV scenario is based on the Green Legacy Initiative (GLI) program, which was launched in 2019 by the Ethiopian government to regreen the country by initiating massive tree seedling plantations (Beyene & Shumetie, 2023; Fikreyesus et al., 2022). These two scenarios were selected after identifying the land use characteristics of the study watershed, available data for land use drivers, and reviewing studies related to scenario-based simulations conducted in Ethiopia (Gebresellase et al., 2023; Kassa et al., 2022; Mohamed & Worku, 2020). This study differs from previous studies conducted in the Gumara watershed: (1) it employed the RF algorithm, which is a robust machine learning LULC classifier, and (2) it provided scenario-based future LULC predictions for the near future and far future periods.

4.2. Materials and Methods

4.2.1. Study Area

This study was conducted in the Gumara watershed, which is a subwatershed of the Lake Tana subbasin in the Upper Blue Nile Basin (UBNB) of Ethiopia (Figure 4.1). The watershed boundary lies between 11°35' N–11°55' north latitude and 37°30' E–38°15' east longitude. The main river of the watershed is the Gumara River, which originates from the Guna Mountains and drains into Lake Tana. The total drainage area of the watershed delineated using the 30 m × 30 m digital elevation model (DEM) is approximately 1425 square kilometers (km²). The elevation of the watershed generally ranges between 1782 and 3712 m above mean sea level (amsl) (Figure 4.1c). The watershed is characterized by a mountainous terrain with a steep gradient in the upstream part and an undulating terrain with a gentle gradient in the downstream part of the watershed (Wubie et al., 2016). Climatologically, the watershed experiences a long rainy season from June to September, with an average annual areal rainfall of 1445 mm. The average annual temperature of the watershed is approximately 20.5 °C. The lowland part of the watershed is prone to flooding in the wet season (June to September), and it also deposits eroded soil from upland subwatersheds (Tegegne & Melesse, 2020). In the watershed, cultivated land is the major LULC class and accounts for more than 75% of the watershed area; the remaining watershed area is covered with grassland, shrublands, forests, and settlements (Chakilu & Moges, 2017). The lower part of the watershed adjacent to Lake Tana is known for rice cultivation (Desta et al., 2019). In watersheds, rapid transitions of grassland, shrubland, and forest to cropland have been observed in recent decades. The majority of the watershed is dominated by rural kebeles with scattered settlements, and their livelihood is based on mixed farming systems by growing crops (teff, rice, wheat, barley, maize, beans, oats, potatoes, etc.) and raising livestock (goats, sheep, cattle, hens, etc.) (Wubie et al., 2016). In addition, watersheds have the potential for growth in different sectors, such as agroindustry, ecotourism, agroforestry, livestock, and energy (Tefera & Kassa, 2017). The watershed under study was selected because it is prone to soil erosion and flooding as a result of intensive agricultural cultivation, as shown in previous studies (Tegegne et al., 2021; Tikuye et al., 2023).

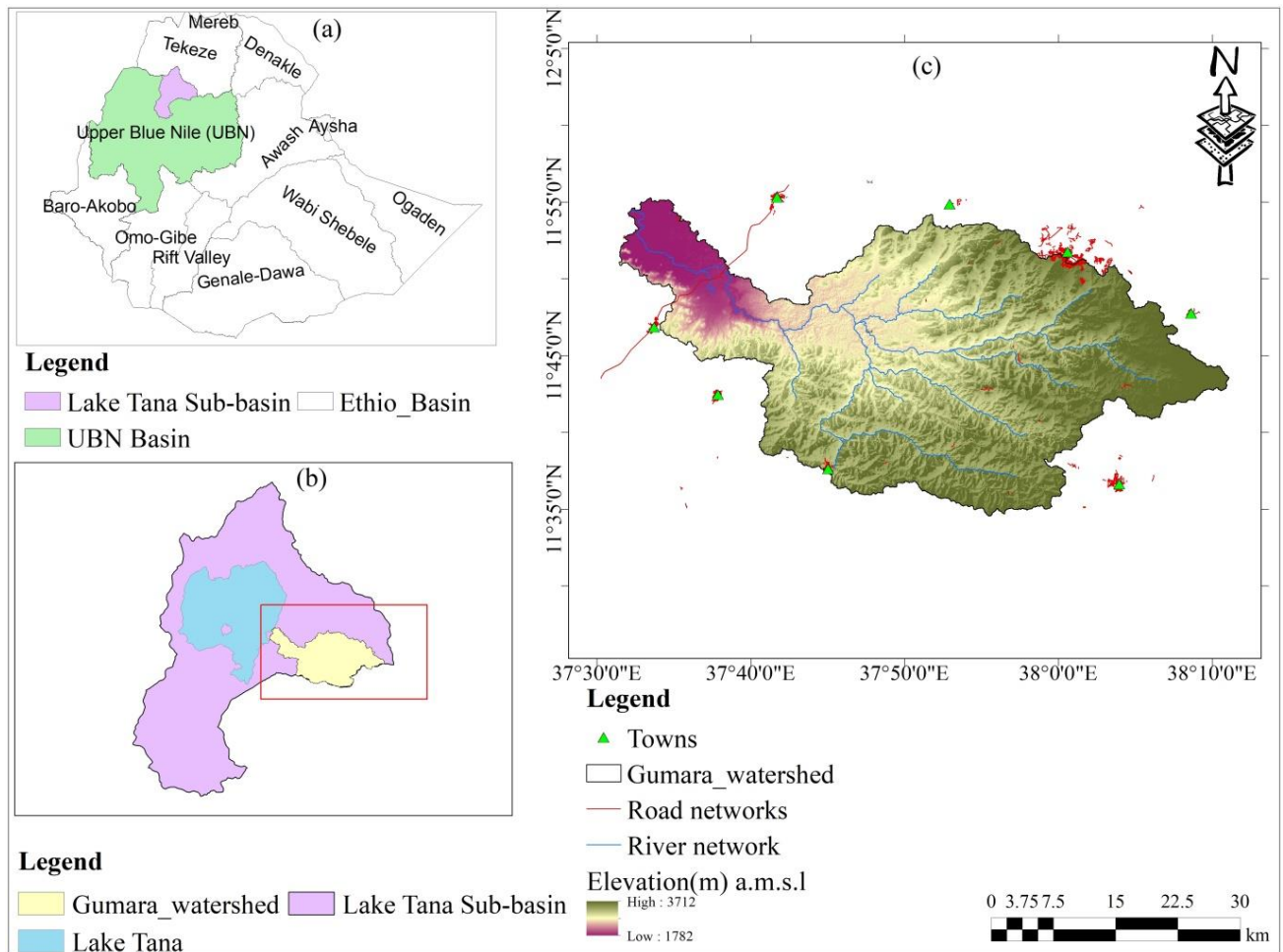


Figure 4.1. Location map of the study area: (a) river basins of Ethiopia, Upper Blue Nile Basin, and Lake Tana subbasin; (b) Lake Tana subbasin, Lake Tana, and Gumara watershed; and (c) Gumara watershed boundary, location of towns, road networks, river networks, and elevation map of the Gumara watershed.

4.2.2. Data Used

LULC maps of the study watershed were prepared using surface reflectance (SR) image collections from Landsat-5/Thematic Mapper (TM) for 1985, 2000, and 2010 and from Landsat-8/Operational Land Imager (OLI) for 2019. The images were accessed from the U.S. Geological Survey website via the GEE data catalog. Table 4.1 presents a description of the Landsat images used for LULC classification of the Gumara watershed. In the GEE environment, the images were filtered by the area of interest (AOI), the date of acquisition, and the percentage of cloud cover (less than 1%).

Table 4.1. Description of Landsat surface reflectance images used for LULC classification of the Gumara watershed.

Landsat Image	Date of Acquisition	Path/Row	No. of Image	Resolution (m)
Landsat-5/TM	1 January–30 April 1985	169/052	6	30
Landsat-5/TM	1 January–30 March 2000	169/052	6	30
Landsat-5/TM	1 January–30 March 2010	170/052	3	30
Landsat-8/OLI	1 January–30 March 2019	169/052	6	30

In LULC classification using the SML algorithm, training and testing stages are important. For this study, training and testing data were collected through a field survey using a global positioning system (GPS) from January to February in 2022. Additionally, high-resolution historical satellite images from Google Earth Pro and Collect Earth Online (CEO) (Saah et al., 2019) were used to collect training and testing points. On this basis, points and polygons were randomly collected for each LULC class identified in Table 4.2. Accordingly, a total of 1784, 2226, 2910, and 2729 points were collected for the years 1985, 2000, 2010, and 2019, respectively. For classification, the shapefiles of the collected training/testing data were imported as assets into the GEE environment. Furthermore, other LULC change-driving variables, such as elevation, slope, distance from roads, distance from streams, and distance from towns, were collected from different sources and processed using ArcGIS 10.4. The distance from roads was derived from the shapefile of road network data acquired from the OpenStreetMap database (<https://www.openstreetmap.org/#map=10/11.9090/38.2297>, accessed on 2 February 2022). The distance from streams and the distance from towns were derived from the shapefiles of the stream network and town location, respectively. The elevation and slope were derived from the 30 m resolution DEM of the Shuttle Radar Topography Mission (SRTM).

Table 4.2. Description of identified LULC classes in the Gumara watershed.

LULC Class	Description
Forest	Areas covered with open forest, dense forest, and woodland. This class mainly includes Eucalyptus tree and other woody plantations of the watershed.
Shrubland	Area of land covered with open and closed bushes and shrubs mainly found along the banks of rivers and streams, degraded and bare lands with sparse vegetation cover.
Grassland	Areas covered with grasslands mainly used for grazing, grassy wetlands, grassy water bodies during dry season.
Cultivated land	Areas of agricultural land mainly used for crop cultivation. It also includes rice cultivation which concentrates at wetland part of the watershed.
Settlement	Areas of urban and rural settlements and other developments like roads.

4.2.3. Overview of the Methodology

This study mainly comprises two main sections: (1) LULC classification and change detection and (2) future LULC prediction. The first section was mainly focused on LULC classification for the years 1985, 2000, 2010, and 2019 and change detection (1985–2000, 2000–2010, 2010–2019, and 1985–2019), as presented in Figure 4.2a. In this section, satellite image collection (Landsat-5/8), filtering image collection (by area of interest, date of acquisition, and metadata), computation of the median composite of filtered image collection, preparation of input variables (vegetation indices and topographic variables), collection and merging of training points, sampling region by integrating the median composite and merged training points, classification using the RF algorithm, accuracy assessment, and exporting of classified images were performed in the GEE environment. As GEE is a petabyte cloud-based platform, it makes image processing and classification easier without downloading the input satellite images (Xiong et al., 2017). Mapping of exported LULC images and change detection were performed using ARC-GIS 10.4. In this study, a change detection starting year (1985) was selected since substantial land use change was observed in most parts of Ethiopia during this year following the land reform proclamation of 1975.

The second section of this study focused mainly on future LULC predictions, as presented Figure 3.4b, for the years 2035 and 2065. For this section, classified images from the first section and LULC change driver variables processed in ArcGIS 10.4 were used as inputs for the LULC prediction model. For the prediction, the CA–Markov model was employed because it combines the temporal prediction power of the Markov model with the spatial prediction power of the CA model. The procedures of this section were as follows: (1) preparation of input data (historical classified images and LULC change driver variables); (2) computation of transition probability matrices (TPMs) using the Markov model; (3) computation of transition suitability maps (TSMs); (4) prediction of LULC maps using the CA–Markov model for the reference year (2019); (5) validation of the CA–Markov model using the predicted and reference map of the year (2019); and (6) prediction of future LULC under the BAU and GOV scenarios for the years 2035 and 2065. In this study, LULC prediction years (2035 and 2065) were selected to examine the land use dynamics of the study watershed in the near future and in far future years.

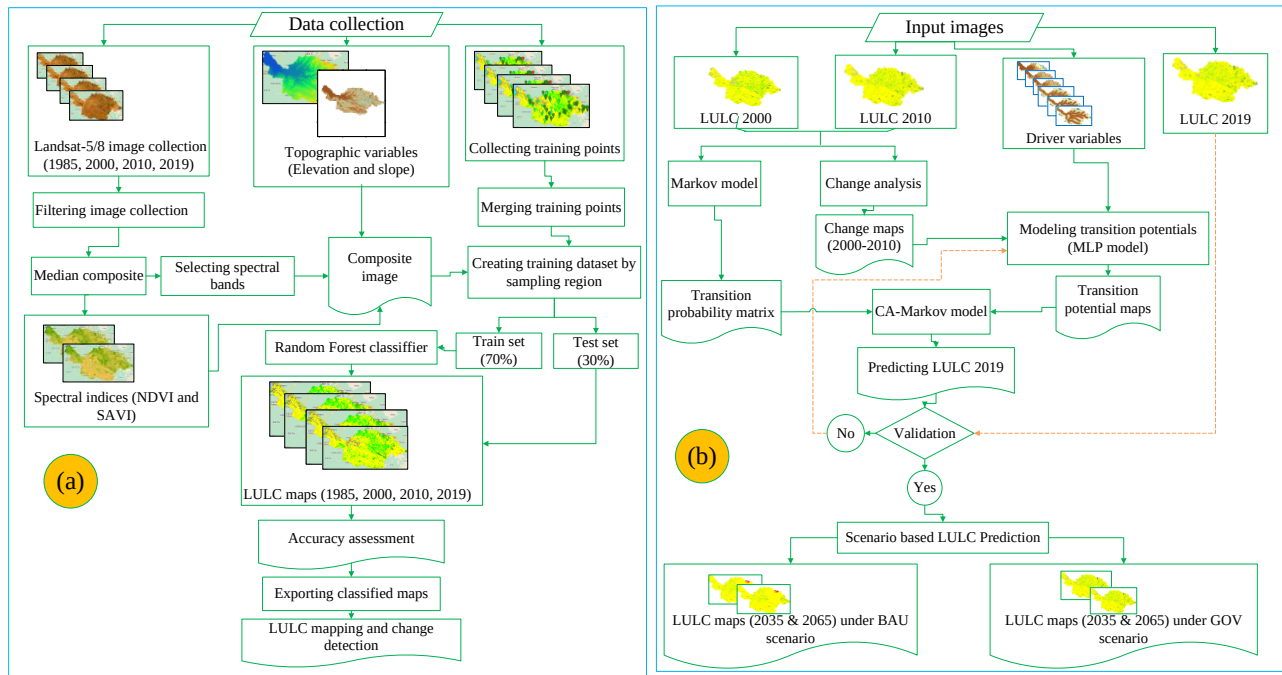


Figure 4.2. Methodological framework of the study: (a) LULC classification and change detection, and (b) LULC prediction.

4.2.4. LULC Classification and Change Detection

The following subsections discuss the details of LULC classification using the RF algorithm in the GEE environment, including variable selection, variable importance, classification accuracy assessment, and change detection methods.

4.2.4.1. LULC Classification

Among several classification algorithms available in the GEE environment, the RF algorithm, which was proposed by Breiman, (2001), was used for this study. As stated in previous studies (Abdi, 2020; Lukas et al., 2023), RF has gained popularity for image classification for a number of reasons: (a) it is capable of handling high-dimensional datasets; (b) it speeds up classification processes by selecting the most important variables; (c) it is an ensemble method; and (d) recent studies conducted on comparative analysis of classification algorithms have reported the superiority of RF over other SML algorithms for areas where agricultural cultivation is most dominant (Adam et al., 2014; Thanh Noi & Kappas, 2017). In addition, compared to other ML classification algorithms, RF requires a minimum number of parameters to be tuned. In LULC classification using SML algorithms, it is mostly recommended to use a larger percentage of the data for training than for testing to improve the performance of the classifier and to enhance the classifier to learn more about the spectral signatures of different LULC classes (Kadri et al., 2023; Shafizadeh-Moghadam et al., 2021; Tassi & Vizzari, 2020). For this reason, the RF algorithm was trained using 70% of the ground truth data, and the

accuracy of the classification was tested using 30% of the ground truth data. To split the data into training and testing sets, the “randomColumn()” function of GEE was used. For classification, the “smileRandomForest()” function of GEE was used. In the GEE environment, the “smileRandomForest()” function requires two main input parameters (N_{tree} and V_{split}). For this study, optimized values of these two parameters were estimated considering the classification accuracy and values of the parameters used in previous studies (Mananze et al., 2020; Talukdar et al., 2020). Accordingly, N_{tree} was found to be 200, and V_{split} was found to be 3, which is approximately the square root of the number of input variables. Using these optimized parameters of the RF algorithm, LULC classification was performed for the four historical years (1985, 2000, 2010, and 2019). Based on this, five LULC classes were identified for the Gumara watersheds, as shown in Table 4.2.

4.2.4.2. Input Variables

The spectral bands SR_B1 to SR_B5 and SR-B7 for Landsat-5/TM and SR_B2 to SR_B7 for Landsat-8/OLI were used as the input variables for the RF classifier. In addition to the spectral bands, vegetation indices and topographic factors (elevation and slope) were used to improve the classification accuracy. For the vegetation indices, the normalized difference vegetation index (NDVI) and soil adjusted vegetation index (SAVI) were used for this study. The NDVI is the most widely used indicator of vegetation greenness (Rouse et al., 1974). The NDVI values ranged from -1 to 1 ; low NDVI values (less than or equal to 0.1) corresponded to areas of bare land, rock, water, sand, or snow; moderate NDVI values (0.2 to 0.5) corresponded to sparse vegetation cover; and high NDVI values (greater than or equal to 0.6) corresponded to dense vegetation cover. The SAVI is a modified version of the NDVI that considers the effect of soil reflectance (Huete, 1988). In the SAVI expression (Equation (1)), L takes different values depending on vegetation cover, where $L = 1$ in areas with no green vegetation cover, $L = 0.5$ in areas with moderate green vegetation cover, and $L = 0$ in areas with very high vegetation cover (which is equivalent to the NDVI equation). For this study, $L = 0.5$ was used considering the vegetation cover of the study watershed. Here, all the indices were computed in the GEE environment using the final median composite of the Landsat-5/8 images by applying equations (3.1) and (3.32). Figures 4.3 and 4.4 show the computed spectral indices of the Gumara watershed for 1985, 2000, 2010, and 2019.

$$NDVI = \frac{NIR-RED}{NIR+RED} \quad (4.1)$$

$$SAVI = \left(\frac{NIR-RED}{NIR+RED+L} \right) * (1 + L) \quad (4.2)$$

where NIR is the near-infrared band (770–895 nm) and RED is the red band (630–690 nm).

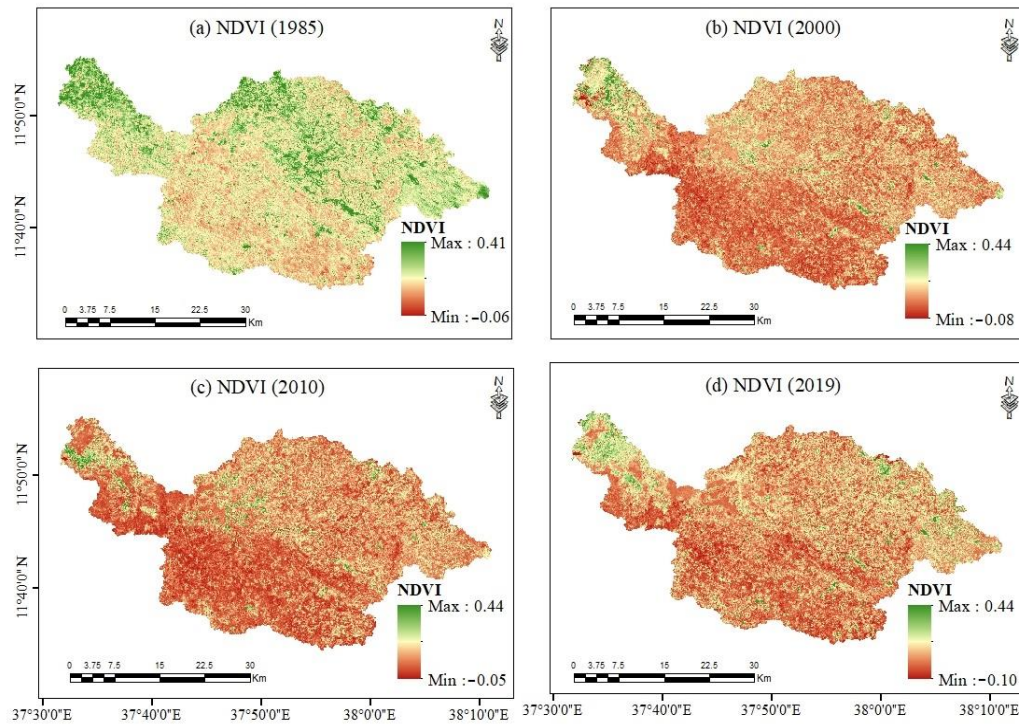


Figure 4.3. Computed NDVI images of the Gumara watershed for the years (a) 1985, (b) 2000, (c) 2010, and (d) 2019.

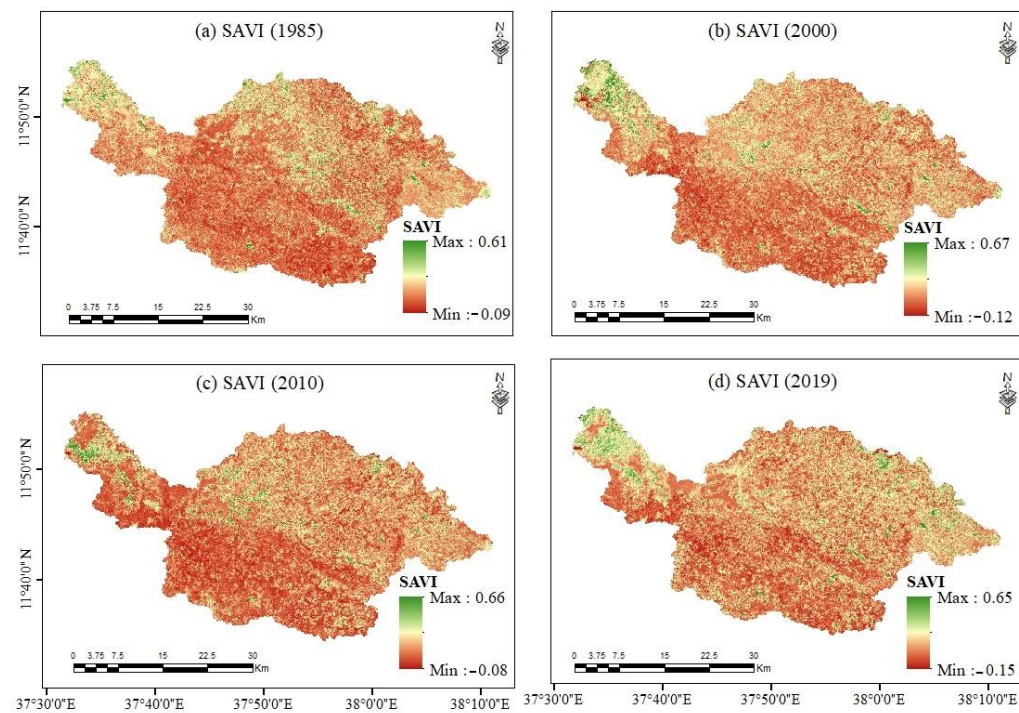


Figure 4.4. Computed SAVI images of the Gumara watershed for the years (a) 1985, (b) 2000, (c) 2010, and (d) 2019.

4.2.4.3. Variable Importance

In this study, a total of 10 variables, which included spectral bands, vegetation indices, and topographic factors, were used to train the RF algorithm as mentioned above (Section 2.4). In this case, all the input variables are not equally important when training the RF algorithm. In other words, each input variable has a different importance in separating one LULC class from another. Therefore, the impact of variables on LULC classification must be checked by computing variable importance (VI) (Nasiri et al., 2022; Thanh Noi & Kappas, 2017). For this purpose, the “explain()” function of GEE was used to generate the VI for each variable.

4.2.4.4. Accuracy Assessment

In image classification, it is vital to assess the performance of classifiers using test/validation datasets to determine whether the classification result is poor, satisfactory, or strong (Congalton & Green, 2019; Foody, 2002). For this study, a confusion matrix was produced in the GEE environment and exported as a comma-separated value (CSV) to evaluate the accuracy of the RF classifier. The accuracy was evaluated using the most widely used accuracy metrics, such as producer accuracy (PA), user accuracy (UA), overall accuracy (OA), and the kappa coefficient (K). Following Foody (2002), PA, UA, OA, and K can be determined using equations (4.3)–(4.6).

$$PA(\%) = \frac{X_{ij}}{x_{i+}} * 100 \quad (4.3)$$

$$UA(\%) = \frac{X_{ij}}{x_{+i}} * 100 \quad (4.4)$$

$$OA(\%) = \frac{\sum_{i=1}^r X_{ii}}{N} * 100 \quad (4.5)$$

$$K = \frac{N \sum_{i=1}^r X_{ii} - \sum_{i=1}^r x_{i+} * x_{+i}}{N^2 - \sum_{i=1}^r x_{i+} * x_{+i}} \quad (4.6)$$

where r is the number of rows in the confusion matrix, X_{ij} is the data in row i column j , X_{ii} is the number of correctly classified data in row i and column i (diagonal entries), x_{i+} is the marginal total of row i , x_{+i} is the marginal total of column i , and N is the total number of data points.

4.2.4.5. LULC Change Detection

LULC change detection analysis is important for determining the amount and type of land use changes that occurred over certain study periods. Among several change detection approaches, post-classification change detection (PCCD), or map-to-map comparison approaches, was employed for this study. This approach is most widely applied for comparing classified maps of different years

(Braimoh, 2006; Yuan, 1999). In this study, for each of the LULC class percentage changes and rates of change for the four periods of 1985–2000, 2000–2010, 2010–2019, and 1985–2019 were computed to detect LULC changes in the study watershed using equations (4.7) and (4.8).

$$P\Delta(\%) = \frac{A_2 - A_1}{A_1} * 100 \quad (4.7)$$

$$R\Delta(\text{km}^2/\text{year}) = \frac{A_2 - A_1}{t} \quad (4.8)$$

where $P\Delta$ is the percentage change, $R\Delta$ is the rate of change, A_1 is the area of the LULC class in km^2 in the initial year, A_2 is the area of the LULC class in km^2 in the final year, and t is the time interval of the period. Additionally, the amount of gain, loss, and net change were computed for each class in the four periods following the methodology provided in (Pontius et al., 2004).

$$\text{Gain}(\text{km}^2) = CT - D \quad (4.9)$$

$$\text{Loss}(\text{km}^2) = RT - D \quad (4.10)$$

$$\text{Net change}(\text{km}^2) = \text{Gain} - \text{Loss} \quad (4.11)$$

where CT is the column total, RT is the row total, and D is the diagonal value of each LULC class that showed persistence.

4.2.5. LULC Prediction

Among the available future LULC prediction models, the combined cellular automata (CA) and Markov chain (CA–Markov) model has been frequently used in several studies (Asif et al., 2023; Beroho et al., 2023; Kafy et al., 2021; Liping et al., 2018). This is because the CA–Markov model integrates the CA model for simulating the spatial dynamics of LULC changes and the Markov chain model for predicting the transition probabilities of LULC classes from one category to another over a certain period (Halmy et al., 2015; Tadese et al., 2021). For this study, the main procedures followed to construct LULC maps of the Gumara watershed for the years 2035 and 2065 using the CA–Markov model available in the land change modeler (LCM) module of IDRISI Selva 17.0 are discussed in the following subsections.

4.2.5.1. LULC Change Driver Variables

There are many variables that drive LULC changes, which are related to land use policy, demographic distribution, socioeconomic development, climate change and variability, and topography (Berihun et al., 2019b; Navin & Agilandeewari, 2020; Vu & Shen, 2021). However, these variables should be selected considering the specific conditions/characteristics of the study area. Based on these data, the

elevation, slope, distance from streams, distance from roads, distance from towns, and evidence of likelihood of change were selected for this study, as illustrated in Figure 4.5. Elevation and slope were selected because these variables are important for determining suitable areas for cultivated land. The distance-to-socioeconomic development variables, such as distance from towns, distance from roads, and distance from streams, were selected because these variables mainly influence the location of settlements. Here, the smaller the distance to towns, roads, or streams, the greater the possibility for the LULC class to be converted to a settlement area. Evidence of the likelihood of change was also selected to determine the probability of disturbance or to explain the change that occurred during the study period. In addition to the variables discussed here, population density is also a significant factor driving land use change. However, due to a lack of reliable census data, this factor was not considered in the present study. For this study, the variables presented in Figure 4.5a–e were processed in ArcGIS 10.4 using the Euclidean distance and surface function of the spatial analyst tool, while the evidence likelihood (Figure 4.5e) was processed in the land change modeler (LCM) module of IDRISI Selva 17.0. In the LCM module, driver variables can be modeled as dynamic or static. In this study, distance to roads, towns, and streams and evidence of likelihood of change were modelled as dynamic variables to account for new developments in infrastructure in future years, whereas elevation and slope were modelled as static variables (Eastman, 2009). To facilitate future land use prediction, all the variables presented in Figure 4.5 were converted to the same pixel size (30×30 m), number of columns and rows (2398, 1279), and projection (WGS 1984 UTM Zone 37 N).

The quantitative association between the LULC changes and the driver variables was checked using Cramer's V test (Cramér, 1999). According to Cohen (2013) the value of Cramer's V ranges between 0 and 1, with a high Cramer's V indicating good explanatory power of the variable. In this test, the p value also indicates the probability that Cramer's V value does not significantly differ from 0. Thus, a low p value is a good indicator that Cramer's V value should not be rejected, while a high p value is also a sure that the test is rejected.

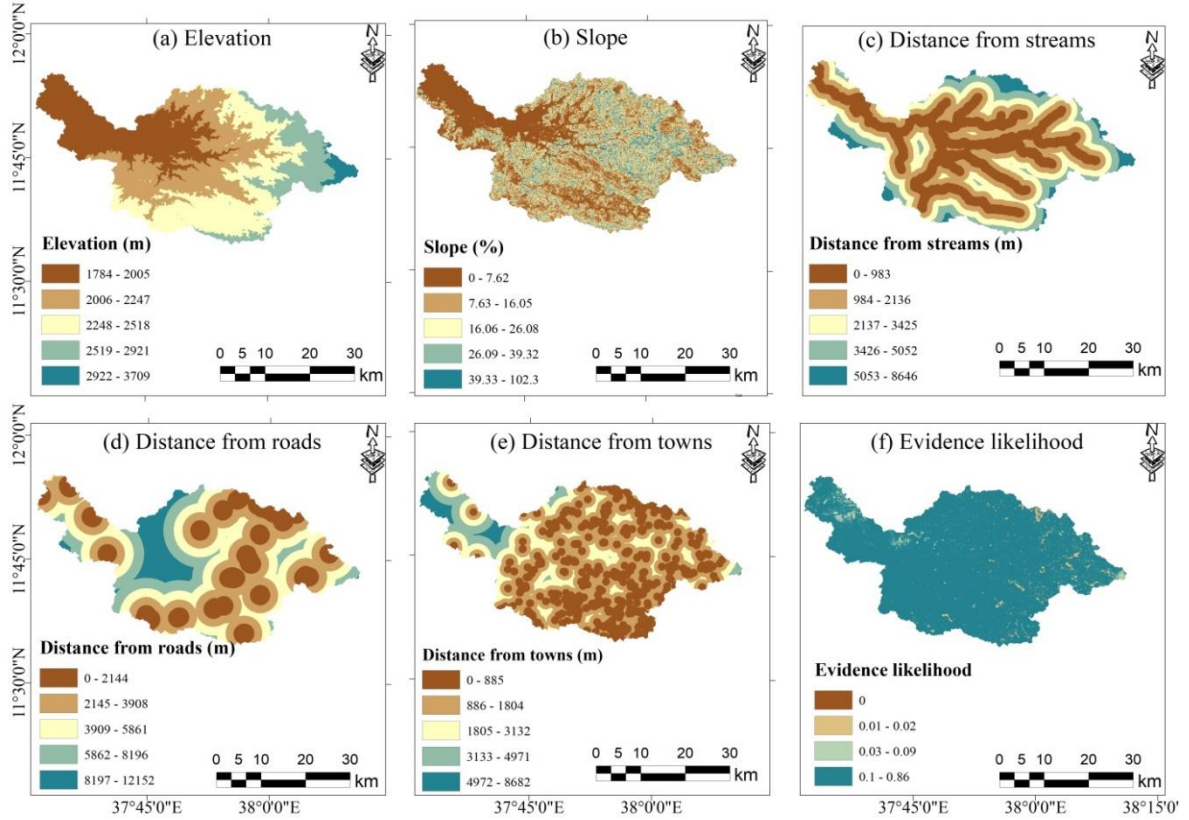


Figure 4.5. Map of driver variables: (a) elevation, (b) slope, (c) distance from streams, (d) distance from roads, (e) distance from towns, and (f) evidence likelihood.

4.2.5.2. Transition Probability Matrix (TPM)

Markov chain analysis is mostly applied for simulating complex processes by considering the initial and final states from an available set of states (Arfasa et al., 2023; Liping et al., 2018). In the Markov chain model, the recent state of LULC (S_y) transforms to another state (S_{y+1}) at the next time, with the possibility indicated by the transition probability matrix (P_{jk}) (equations (4.12)–(4.14)).

$$S_{y+1} = P_{jk} * S_y \quad (4.12)$$

$$P_{jk} = \begin{bmatrix} P_{11} & P_{12} & \dots & P_{1n} \\ \vdots & \vdots & & \vdots \\ P_{n1} & P_{n2} & & P_{nn} \end{bmatrix} \quad (4.13)$$

$$0 \leq P_{jk} \leq 1 \text{ and } \sum_{i=1}^n P_{jk} = 1, i, j = 1, 2, 3 \dots n. \quad (4.14)$$

where P_{jk} is the transition probability matrix, which describes the likelihood of changing LULC from the (j) category to the (k) category in the LULC class at time S_y LULC; (y); S_{y+1} is the predicted LULC map at time ($y + 1$); and n is the number of LULC classes. A low value of the transition

probability (approach to 0) indicates a decreased possibility of transition, while a high transition probability (approach to 1) indicates a high possibility of transition of a particular class to another (Faichia et al., 2020). For this study, the transition probability matrices were computed for the periods from 1985 to 2000, 2000 to 2010, 2010 to 2019, and 1985 to 2019. Afterwards, the generated TPMs were used to construct LULC maps for future years (for 2035 and 2065).

4.2.5.3. Transition Suitability Map (TSM)

In LULC prediction, the TSM provides information on the suitability of LULC for converting one class of cells to another (Abbas et al., 2022; Leta et al., 2021b). In the LCM module of IDRISI Selva 17.0, the three most popular supervised machine learning algorithms, logistic regression (LR), similarity-weighted instance-based machine learning (SimWeight), and MLP-ANN, were used for generating TSMs. Among these algorithms, the MLP was used for this study since it is capable of modelling nonlinear relationships between dependent and independent variables (Eastman, 2009). In addition, multiple transition maps can be generated at once without the intervention of the modeler. The algorithm works as a feedforward ANN with one directional flow of data between the input, hidden, and output layers (Camargo et al., 2019; Kamaraj & Rangarajan, 2022). To generate the TSMs, historical LULC change patterns were used as the dependent variable, and topographic data (elevation and slope) and other proximity/distance-related driving factors were used as the independent variables (Section 3.2.5.1). For this study, the LULC TSMs were generated for the same periods as the TPM, considering the most dominant LULC transition by setting a transition threshold of 2 km² in the LCM module. Based on these data, six dominant transitions, which included (1) transition from forest to shrubland, (2) forest to cultivated land, (3) shrubland to forest, (4) shrubland to cultivated land, (5) grassland to cultivated land, and (6) cultivated land to settlement, were identified. The reliability of the generated transition potential maps was evaluated by checking the accuracy of the MLP algorithm, where an accuracy greater than 80% was considered acceptable (Eastman, 2009).

4.2.5.4. CA–Markov Model

As mentioned in Section 3.2.5.2, Markov chain analysis is important for estimating the TPM between earlier and later LULC maps. However, the model neglects spatial explicitness, and it does not provide information on the likely spatial distribution of LULC transitions (Hamad et al., 2018). Hence, by integrating CA with the Markov chain, this limitation can be overcome since the CA model uses spatial contiguity elements in its model structure (Faichia et al., 2020; Liping et al., 2018). CA is a bottom-up dynamic model that is mainly applied for spatiotemporal computations (Liping et al., 2018). The model contains the cell space, cell, neighbors, set of rules, and time (Beroho et al., 2023). In the model, the

neighbors can be identified by providing a contiguity filter to the CA model. It can simulate LULC changes over a certain time by using a set of rules that govern how a cell can change according to its initial state and its neighborhood, as expressed in equation (4.15).

$$S_{y+1} = f(S_y, N) \quad (4.15)$$

where S_{y+1} is the later state that is predicted from the LULC map at time $(y + 1)$; S_y is the initial state or the base LULC map at time (y) ; N is the neighborhood of each cell; and f is the governing transformation rule for the local space. In this study, future LULC maps of the Gumara watershed were generated for the years 2035 and 2065 using the CA–Markov model, which is available from IDRISI Selva 17.0. For prediction, earlier and latter LULC maps, Markov chain TPMs, and TSMs were used as inputs to the CA–Markov model.

4.2.5.5. Validation of the CA–Markov Model

In geospatial simulation, model validation is used to evaluate the accuracy, functionality and reliability of prediction performance (Ruben et al., 2020). For this study, model validation was performed by comparing the predicted LULC map from 2019 with the reference LULC map from 2019. To predict the 2019 LULC map, the CA–Markov model used the 2010 LULC map as the base year, along with the transition probability matrix and transition suitability maps derived from the LULC changes between 2000 and 2010. For evaluation, commonly used kappa coefficients, namely, kappa for no information (K_{no}), kappa for location ($K_{location}$), and kappa for standard ($K_{standard}$), were computed using the “VALIDATE” module in IDRISI Selva 17.0. According to Congalton (2001), a kappa coefficient less than 0 indicates no agreement, 0 to 0.2 indicates slight agreement, 0.2 to 0.41 indicates fair agreement, 0.41 to 0.60 indicates moderate agreement, 0.60 to 0.80 indicates substantial agreement, and 0.81–1.0 indicates perfect agreement.

4.2.5.6. Scenario-Based LULC Prediction

Recently, scenario-based (“what-if”) prediction of future LULC has become a hot topic of research in the geospatial scientific community for identifying future land use dynamics under different socioeconomic conditions (Beroho et al., 2023; Chang et al., 2021; Gebresellase et al., 2023; Hamad et al., 2018). This scenario-based LULC prediction can serve as a robust tool for making and implementing decisions related to land use policies. For this study, two scenarios, (1) BAU and (2) GOV, were considered to predict the future LULC conditions of the Gumara watershed. These two scenarios were selected considering (1) the aim of the study, (2) the current land use conditions of the study watershed, (3) the availability of data for setting the scenarios, and (4) the future plans of the

country Ethiopia (for example, the GLI program). The scenarios considered for this study were the same as the scenarios used in recent work of (Gebresellase et al., 2023), which was conducted in the Upper Awash Basin of Ethiopia. However, the method used to determine the transition potential maps was different from this study.

The first scenario (BAU) assumes the continuity of the current trends in LULC changes and socioeconomic development (intensive agricultural cultivation, urbanization, and development infrastructures). The scenario was designed to answer the following question: “What will happen if the current trend of LULC changes and socioeconomic development continue in the future?” (Chang et al., 2021). For this scenario, all the driving variables mentioned in the previous section (Section 2.5.1) and all dominant LULC “from-to” transitions were used to generate transition potential maps in the MLP algorithm. Under the BAU scenario, LULC drivers such as distance to roads, distance to towns, distance to streams, and evidence of likelihood of change were assumed to be dynamic variables to account for the future development of new infrastructure. Topographic factors (slope and elevation) were considered static variables. In this scenario, the expansion of agricultural lands and settlement areas is highly expected.

On the other hand, the second scenario (GOV) considers the GLI Program of Ethiopia. The GLI is a massive tree planting program that was first launched in 2019 with the objective of restoring degraded lands, increasing forest cover and reducing the impact of climate change (Fikreyesus et al., 2022). Following the launch of the program, Ethiopia planted more than 20 billion tree seedlings from 2019 to 2022 and plans to plant 50 billion tree seedlings by 2026 (Beyene & Shumetie, 2023). In general, the objective of the program is to make Ethiopia a green and climate-resilient country (Kassa et al., 2022). In contrast to the BAU scenario, in the GOV scenario, increases in forests and other vegetation cover are expected due to controlled anthropogenic activities. For this scenario, only topographic/static variables (slope and elevation) were considered as driver variables. The other dynamic variables related to infrastructure development were neglected for this scenario. This scenario also assumes restricted transitions of different LULC classes to cultivated land and settlement, but it allows the transition of cultivated land to settlement.

4.3. Results

4.3.1. LULC Classification

Figure 4.6 shows the generated LULC maps of the Gumara watershed with five identified classes (forest, shrubland, grassland, cultivated land, and settlement). Based on the four LULC maps, cultivated land was the most dominant class, followed by shrubland, while settlements exhibited

minimal areal coverage. For instance, in 1985, cultivated land accounted for 58.6%, followed by shrubland (31.72%), forest (5.22%), grassland (4.40%), and settlement (0.06%). In 2019, cultivated land accounted for more than 83.08%, followed by shrubland (12.79%), while forest, grassland, and settlement accounted for 2.59%, 1.36%, and 0.18%, respectively. This shows the significant expansion of cultivated land and settlement at the expense of reductions in shrubland, grassland and forest. As shown in Table 4.3 and Figure 4.7, between 1985 and 2019, the area of cultivated land and settlements significantly increased from 837.79 to 1187.48 km² and from 0.81 to 2.63 km², respectively. Consistently with these findings, (Chakilu & Moges, 2017) reported significant expansion of cultivated lands in the Gumara watershed.

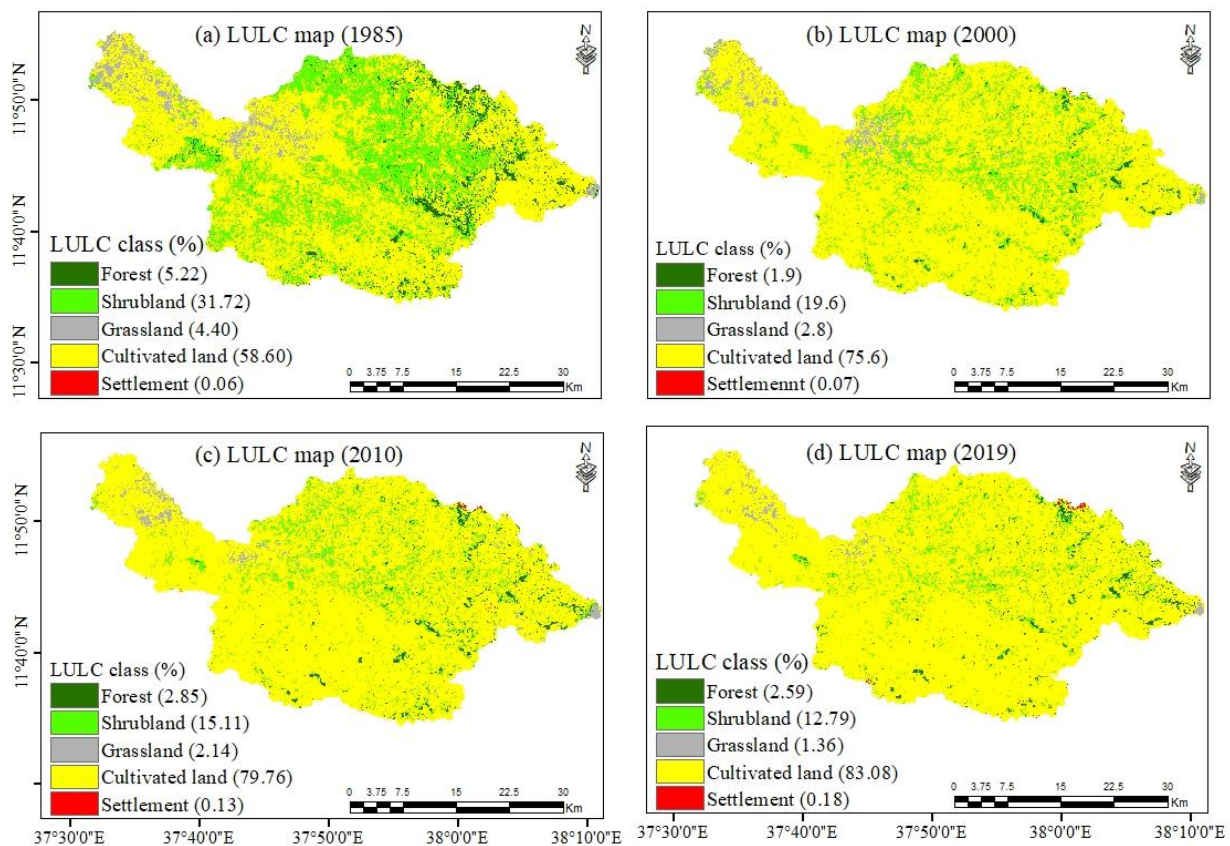


Figure 4.6. LULC maps of the Gumara watershed for (a) 1985, (b) 2000, (c) 2010, and (d) 2019. The values in the legend indicate the percentage of each LULC class.

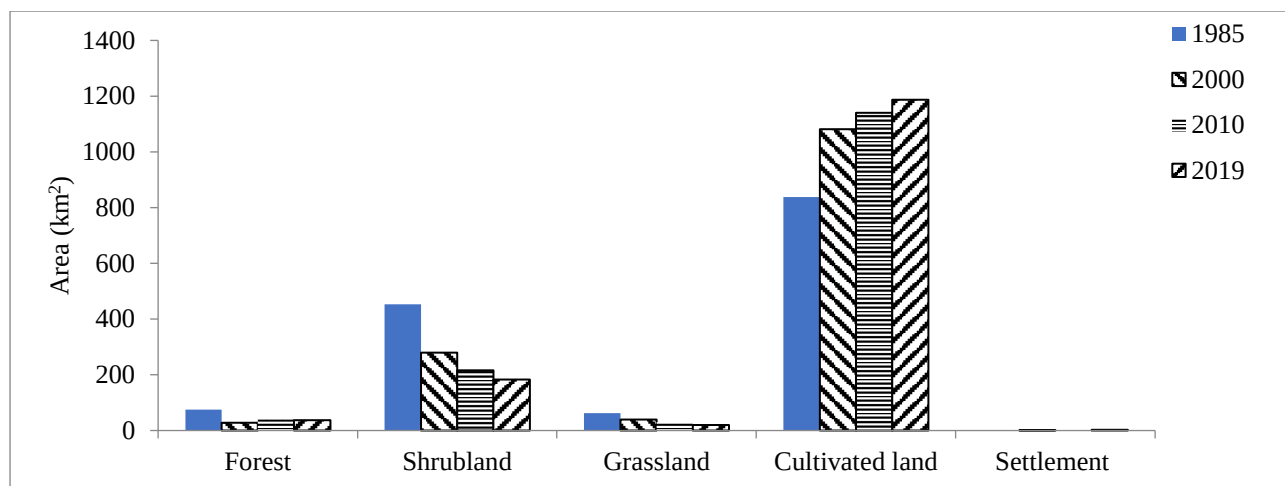


Figure 4.7. Area of each LULC class in the Gumara watershed for the four historical years (1985, 2000, 2010, and 2019).

Table 4.3. Area and percentage of each LULC class in the Gumara watershed for the four historical years (1985, 2000, 2010, and 2019).

LULC Class	Area (1985)		Area (2000)		Area (2010)		Area (2019)	
	(km ²)	(%)	(km ²)	(%)	(km ²)	(%)	(km ²)	(%)
Forest	74.60	5.22	27.62	1.93	40.77	2.85	37.01	2.59
Shrubland	449.49	31.72	280.00	19.58	216.00	15.11	182.81	12.79
Grassland	62.90	4.40	39.96	2.79	30.64	2.14	19.47	1.36
Cultivated land	837.79	58.60	1077.14	75.62	1136.11	79.76	1184.48	83.08
Settlement	0.81	0.06	0.99	0.07	1.88	0.13	2.63	0.18

4.3.2. Accuracy Assessment

Figure 4.8 and Table 4.4 present the results of the accuracy assessment in terms of UA, PA, OA, and K. Based on these results, the overall accuracies of the LULC maps of 1985, 2000, 2010, and 2019 were found to be 94.39%, 94.84%, 93.13%, and 91.13%, respectively (Table 4.4). The kappa coefficients were 0.92, 0.94, 0.90, and 0.88 for the corresponding years, respectively (Table 4.4). Based on the criteria provided in (Congalton, 2001), all of the LULC maps showed perfect agreement with the validation dataset, with a kappa coefficient greater than 0.81. The confusion matrices used for accuracy assessment are provided in Appendix B1–B4.

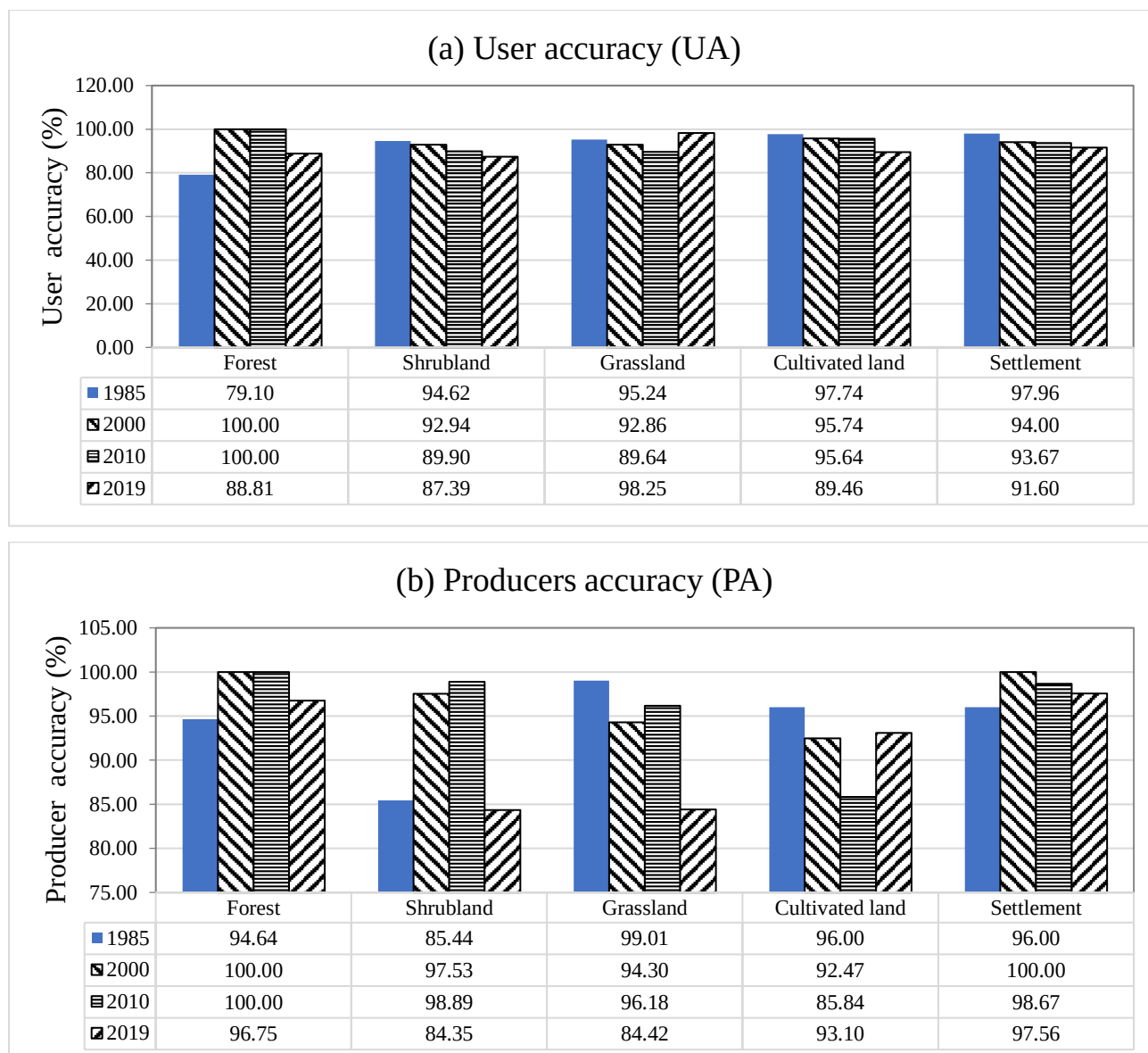


Figure 4.8. (a) UA and (b) PA assessment results for each class for the LULC maps for the years 1985, 2000, 2010, and 2019.

Table 4.4. Results of the classification accuracy assessment in terms of the overall accuracy (OA) and kappa coefficient (K).

LULC Map	Overall Accuracy	Kappa Coefficient	Status of Agreement
1985	94.39	0.92	Perfect agreement
2000	94.84	0.94	Perfect agreement
2010	93.13	0.90	Perfect agreement
2019	91.13	0.88	Perfect agreement

4.3.3. Variable Importance

In this study, a total of 10 variables (6 spectral band Landsat images, 2 vegetation indices and 2 topographic factors) were used to train the RF algorithm. Figure 4.9 shows the relative importance of

these variables used for mapping LULC in the Gumara watershed. Among these variables, elevation was found to be the most important. Consistently with these findings, several studies have reported the importance of vegetation indices and topographic factors in improving LULC classification (Abida et al., 2022; Mananze et al., 2020). Among the vegetation indices, the NDVI was more important than the SAVI in most cases.

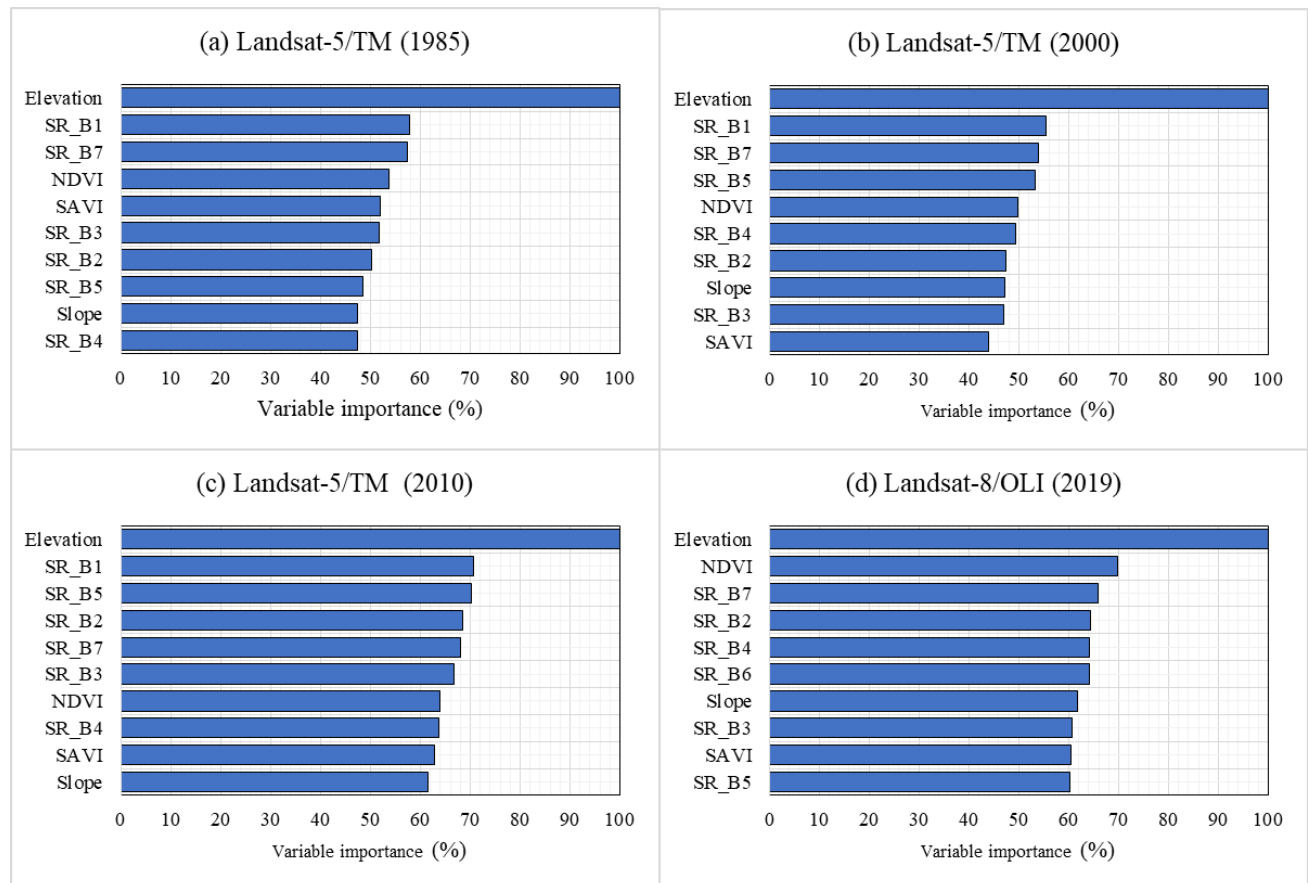


Figure 4.9. Relative variable importance (%) for the four datasets used for mapping LULC in the Gumara watershed: (a) Landsat-5/TM (1985), (b) Landsat-5/TM (2000), (c) Landsat 5/TM (2010), and (d) Landsat-8/OLI (2019).

4.3.4. Change detection (1985–2019)

4.3.4.1. Percentage Change and Annual Rate of Change

Table 4.5 shows the percentage change and annual rate of change in each LULC class. According to the results, shrubland and grassland exhibited negative changes or reductions throughout the study period. Similarly, forestlands exhibited negative changes during all of the periods except for the period from 2000 to 2010. Considering all the percentage change values, the maximum positive change (41.74%) in cultivated land was detected for the period 1985 to 2019, while the maximum negative change (−69.05%) in grassland was detected for the same period. In terms of the rate of change, the

maximum rate of increase (16.22 km²/year) in cultivated land was detected for the period 1985 to 2000, while the maximum rate of decrease (−11.57 km²/year) in shrubland was detected for the same period (1985–2000), as shown in Table 4.5.

Table 4.5. Percent change (PΔ) in (%) and annual rate of change (RΔ) in km²/year for the four study periods.

LULC Class	1985–2000		2000–2010		2010–2019		1985–2019	
	PΔ	RΔ	PΔ	RΔ	PΔ	RΔ	PΔ	RΔ
Forest	−62.98	−3.13	37.64	1.32	−9.24	−0.42	−50.40	−1.11
Shrubland	−38.26	−11.57	−22.86	−6.40	−15.36	−3.69	−59.69	−7.96
Grassland	−36.48	−1.53	−23.33	−0.93	−36.46	−1.24	−69.05	−1.28
Cultivated land	29.05	16.22	5.45	5.90	4.15	5.26	41.74	10.28
Settlement	22.31	0.01	39.32	0.09	40.29	0.08	34.86	0.05

4.3.4.2. Gain, Loss, and Net Change

Table 4.6 shows the gains and losses of different LULC classes in the Gumara watershed for the four study periods computed using the LCM module of IDRISI Selva 17.0. The net change in each LULC class was also computed by taking into account the difference in the gain and the loss. For the first period (1985–2000), gains and losses of (322.28, −80.18), (91.32, −262.25), (23.87, −46.45), and (4, −52.45) km² were observed for cultivated land, shrubland, grassland, and forest, respectively (Table 4.6). For the second period (2000–2010), cultivated land gained 139.77 km², while shrubland and grassland lost 125.20 and 31.16 km², respectively. Similarly, in the other periods, larger values of gains than losses were found for cultivated land and settlement, while smaller values of gains than losses were found for the other classes. For this reason, the net changes were found to be positive for cultivated land and settlement and negative for the other classes (Figure 4.10). For example, for cultivated land, positive net changes of 242.10, 56.31, 49.59, and 348.01 km² were found for the corresponding periods. For shrubland, negative net changes of −170.93, −61, 03, −34.87, and −266.83 km² were found for the corresponding periods. For the forest class, negative net changes were found, with the exception of the second period (2000–2010).

Table 4. 6. Gain and loss of each LULC class for the four study periods.

LULC Class	1985–2000		2000–2010		2010–2019		1985–2019	
	Gain (km ²)	Loss (km ²)	Gain (km ²)	Loss (km ²)	Gain (km ²)	Loss (km ²)	Gain (km ²)	Loss (km ²)
Forest	4.00	52.45	14.58	1.57	8.43	12.01	11.15	50.16
Shrubland	91.32	262.25	64.17	125.20	56.74	91.61	51.74	318.56
Grassland	23.87	46.45	21.29	31.16	9.86	21.72	9.15	53.45
Cultivated land	322.28	80.18	139.77	83.46	113.48	63.88	399.17	51.16
Settlement	0.71	0.57	2.00	0.57	2.29	1.72	2.86	0.71

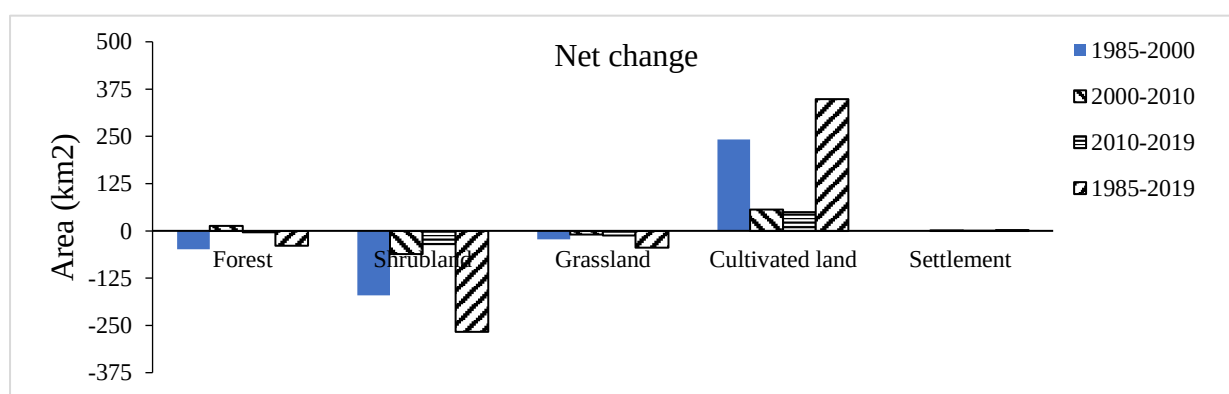


Figure 4.10. Net change (gain-loss) in each LULC class for the four study periods (1985–2000, 2000–2010, 2010–2019, and 1985–2019).

4.3.4.3. Contribution to the Net Change in Cultivated Land

To show the contribution of the four LULC classes to the net change in cultivated land over the study period, four graphs were generated, as shown in Figure 4.11a–d. In all the periods, shrubland was found to be the main contributor to the increase in the net change in cultivated land, followed by grassland. For example, in the first period (1985–2000), 200.54, 22.46, and 21.0 km² area of land were contributed by shrubland, grassland and forest, respectively, to increase the net change in cultivated land area (Figure 4.11a). Similarly, in the fourth period (1985–2019), areas of 280.67, 44.80, and 28.75 km² were contributed by shrubland, grassland, and forest, respectively, to increase the net change in cultivated land by 353.5 km² (Figure 4.11d). Overall, shrubland and grassland contributed to the increase in cultivated land in all four periods. Forests contributed to the increase in the net change in the first and fourth periods (Figure 4.11a,d) and contributed to the reduction in the net change in the second and third periods (Figure 4.11b,c); however, settlements contributed to the reduction in the net change in the second and third periods (Figure 4.11b,c), and they also contributed negligibly to the increase in the other periods.

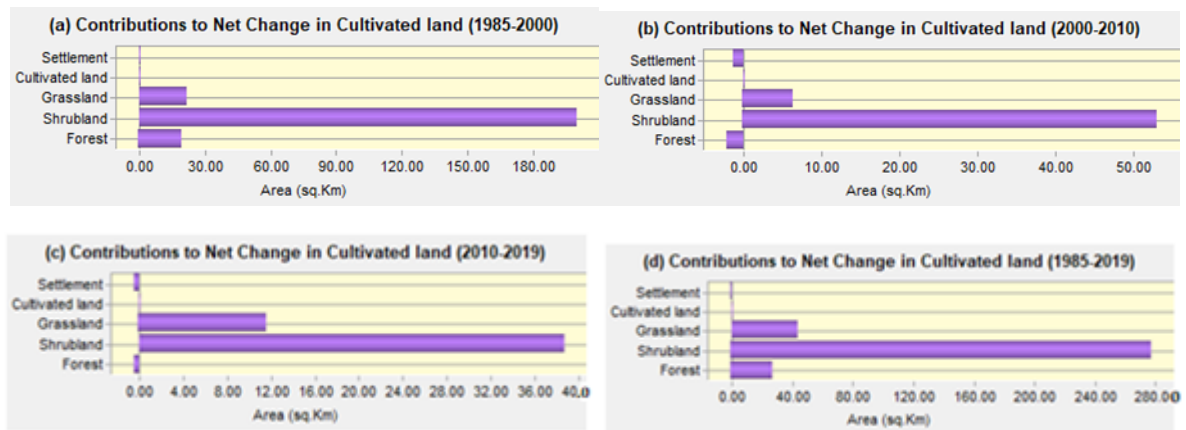


Figure 4. 11. Contribution of each LULC class to the net change in cultivated land: (a) 1985–2000, (b) 2000–2010, (c) 2010–2019, and (d) 1985–2019.

4.3.5. LULC Change Driver Variables

For this study, topography and distance-/proximity-related driver variables that influence LULC changes were considered to generate the TSMs of the most dominant changes that occurred in the study watershed. These driver variables were modelled either as static or dynamic variables in the LCM module of IDRISI Selva 17.0. Before the drivers were used for predicting transition potential or suitability maps, the explanatory power of each variable was evaluated based on Cramer's V and p values (Table 4.7). Although Cramer's V value does not offer strong evidence for describing the explanatory power of the driving variable, it can be taken as a simplified approach to test the influence of the variables (Arfasa et al., 2023; Leta et al., 2021b). Based on the Cramer's V values presented in Table 4.7, the evidence of likelihood (probability disturbance) was found to be the most important variable, as it had the highest Cramer's V value (0.4885). Similarly to these findings, several studies have shown the importance of topographic factors and evidence of likelihood in influencing the spatial distribution of LULC changes (Berihun et al., 2019a; Yesuph & Dagne, 2019).

Table 4.7. Cramer's V values of LULC driver variables.

Driver Variables	Cramer's V	p Value
Elevation	0.2105	0.0000
Slope	0.0437	0.0000
Distance from streams	0.0868	0.0000
Distance from roads	0.1004	0.0000
Distance from towns	0.0521	0.0000
Evidence likelihood	0.4885	0.0000

4.3.6. Transition Probability Matrix (TPM)

In LULC change studies, the TPM shows the probability of conversion of LULC classes from one category to another. For this study, four 5 * 5 Markovian TPMs were generated for the periods from 1985 to 2000, 2000 to 2010, 2010 to 2019, and 1985 to 2019 (Table 4.8a–d) using the Markov module of IDRISI Selva 17.0. In the matrices, the columns show the later or the newer year LULC classes (e.g., the LULC class of 2000), while the rows show the previous or earlier year LULC classes (e.g., the LULC class of 1985). The diagonal values shaded in grey show the proportion of the classes that showed persistence (LULC classes remaining unchanged), whereas the off-diagonal values show the proportion of the LULC classes that changed from one category to another between the earlier and the later years. High percentages of persistence were observed for the cultivated land in the four respective periods, with values of 91.41, 91.48, 93.81, and 96.99%. Similarly, settlements also exhibited persistent proportions of 87.44, 81.17, 82.49, and 81.80% for the corresponding periods. The other LULC classes (forest, shrubland, and grassland) exhibited minimum values of persistence percentages or probabilities. For instance, between 1985 and 2000 (Table 4.8a), persistent percentages of 18.48, 28.88, and 25.97% were observed for forest, shrubland, and grassland, respectively.

Regarding the transition between LULC classes (off-diagonal), high percentages of conversion of shrubland, grassland, and forest to cultivated land were observed in the four periods. For example, high percentages of conversion of shrubland to cultivated land were observed, with values of 69.70, 66.78, 74.32, and 76.91% for the four respective periods, as presented in Table 4.8a–d. Similarly, percentages of 67.47, 76.50, 79.78, and 75.33% were observed for the conversion of grassland to cultivated land (Table 4.8a–d). These results indicate the expansion of agricultural cultivation and settlement areas in the Gumara watershed at the expense of forest, shrubland, and grassland. For this purpose, rapid population growth, demand for wood for charcoal and construction material, and extensive rice cultivation are the main factors influencing the expansion of cultivated land (Desta et al., 2019; Wubie et al., 2016).

Table 4.8. (a) Transition probability matrix of LULC classes in the Gumara watershed: (a) from 1985 to 2000, (b) from 2000 to 2010, (c) from 2010 to 2019, and (d) from 1985 to 2019.

(a)					
1985	2000				
	Forest	Shrubland	Grassland	Cultivated Land	Settlement
Forest	0.1848	0.4651	0.0043	0.3447	0.0010
Shrubland	0.0053	0.2888	0.0087	0.6970	0.0002
Grassland	0.0013	0.0643	0.2597	0.6747	0.0000
Cultivated land	0.0020	0.0614	0.0218	0.9141	0.0007
Settlement	0.0000	0.0048	0.0000	0.1208	0.8744
(b)					
2000	2010				
	Forest	Shrubland	Grassland	Cultivated Land	Settlement
Forest	0.8073	0.0872	0.0017	0.0526	0.0012
Shrubland	0.0710	0.2508	0.0092	0.6678	0.0012
Grassland	0.0072	0.0997	0.1275	0.7650	0.0006
Cultivated land	0.0045	0.0598	0.0191	0.9148	0.0018
Settlement	0.0018	0.0248	0.0071	0.1546	0.8117
(c)					
2010	2019				
	Forest	Shrubland	Grassland	Cultivated Land	Settlement
Forest	0.4571	0.2724	0.0030	0.2653	0.0022
Shrubland	0.0298	0.2198	0.0059	0.7432	0.0013
Grassland	0.0050	0.0305	0.1657	0.7978	0.0010
Cultivated land	0.0051	0.0461	0.0087	0.9381	0.0020
Settlement	0.0036	0.0246	0.0034	0.1434	0.8249
(d)					
1985	2019				
	Forest	Shrubland	Forest	Cultivated Land	Forest
Forest	0.5800	0.1526	0.0020	0.2594	0.0059
Shrubland	0.0082	0.2225	0.0000	0.7691	0.0002
Grassland	0.0006	0.0126	0.2335	0.7533	0.0000
Cultivated land	0.0034	0.0204	0.0051	0.9699	0.0012
Settlement	0.0016	0.0020	0.0000	0.4784	0.8180

4.3.7. Transition Suitability Maps (TSMs)

In this study, the six most dominant “from–to” transition potentials were considered, as discussed in section 4.2.5.3. To predict transition potentials, a feed-forward enhanced MLP neural network model was employed using the IDISI Selva 17.0 LCM module. In this regard, the main outputs of the MLP model are transition potential or suitability maps, which provide information on the suitability for change (Eastman, 2009). As an example, Figures 4.12a & b show the potentials for the transition from

shrubland to cultivated land and from cultivated land to settlement are presented, respectively. Hence, in the region of the watershed indicated by a circular shape, either the expansion of cultivated land or the expansion of settlement areas is highly expected in future years. This part of the watershed includes the town of Debre Tabor, which is the capital of the South Gonder Zone in the Amhara regional state.

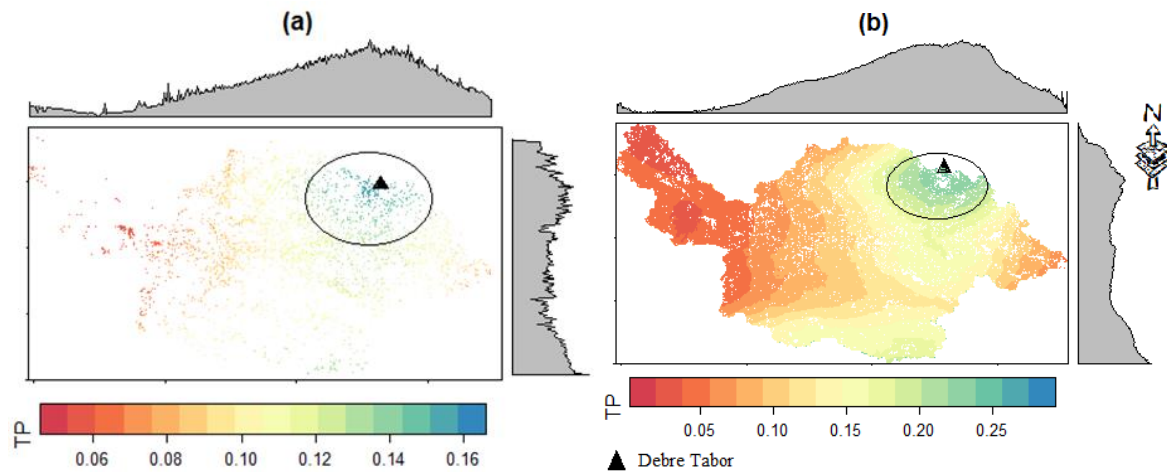


Figure 4.12. Potential for transition: (a) shrubland to cultivated land and (b) cultivated land to settlement. TP is the transition potential. The greater the TP is, the greater the possibility of a transition from one class to another. The gray shaded regions show the orientation gradients of the transition potential.

4.3.8. Validation of the CA–Markov Model

In this study, the performance of the CA–Markov model in predicting future LULC dynamics was evaluated by comparing the reference and predicted (simulated) LULC maps from 2019 (Figure 4.13). For validation, the LULC map of 2019 under the BAU scenario (Figure 4.13b) was generated using the LULC map of 2000 as an earlier image and the LULC map of 2010 as a later image, along with the transition probability matrix and the transition potential maps. Kno, Klocation, and Kstandard were found to be 0.89, 0.86, and 0.94, respectively. These results confirm the high reliability of the CA–Markov model for predicting the future LULC dynamics of the Gumara watershed since all the kappa values are greater than 0.81 based on the criteria provided in Congalton (2001). After evaluating the performance of the CA–Markov model, future LULC maps were predicted under the BAU and GOV scenarios for 2035 and 2065. Figure 4.14 also shows a comparison of the areas of the LULC classes between the reference and predicted maps for 2019. Based on these findings, the areas of the LULC classes are nearly similar except for slight overprediction of the cultivated land and slight underprediction of all the other classes by the CA–Markov model compared to the areas of the LULC classes of the reference map (Figure 4.14). As mentioned above, LULC validation was performed to

evaluate the prediction capability of the CA–Markov model under the BAU scenario only. As the GOV scenario was recently launched by the Ethiopian government in 2019, validation was not performed for this scenario.

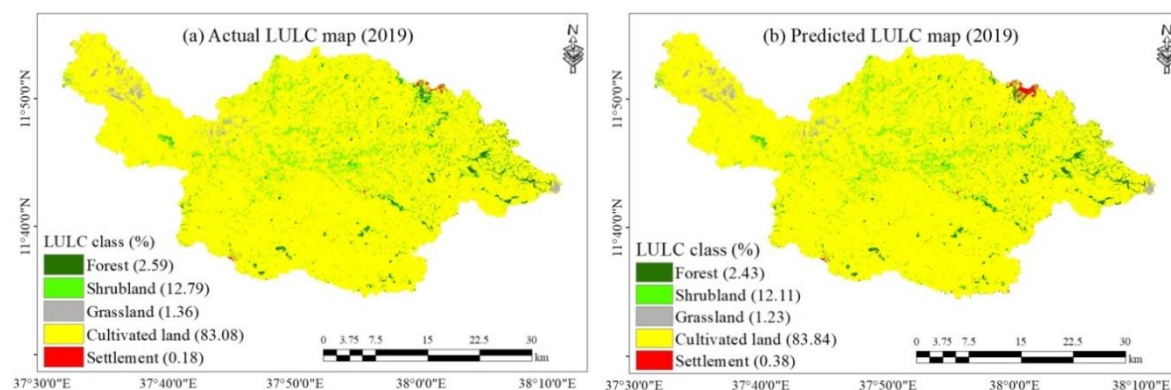


Figure 4.13. LULC maps (2019): (a) reference LULC map and (b) CA–Markov model-predicted LULC map under the BAU scenario.

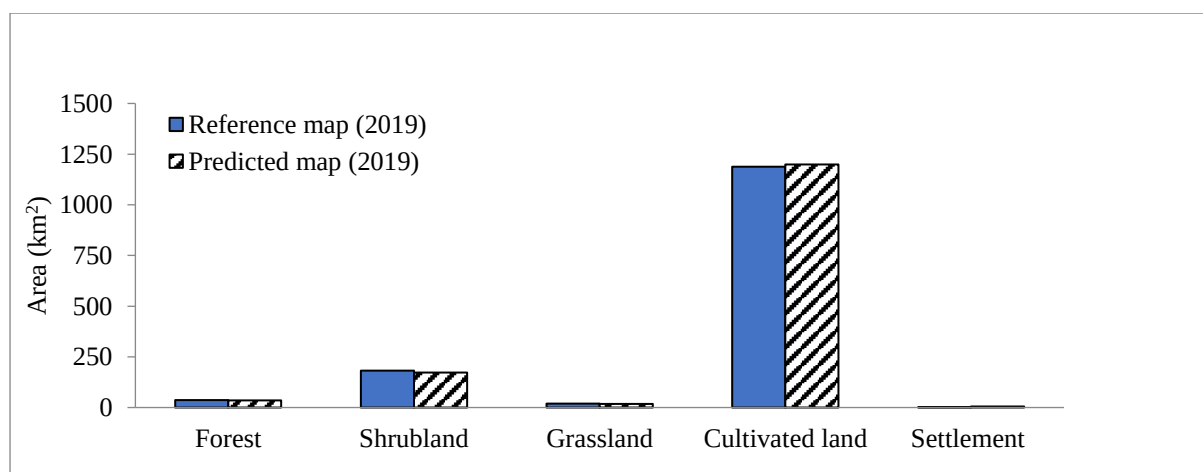


Figure 4.14. Comparison of the reference (baseline) and predicted areas of the LULC classes in the Gumara watershed in 2019.

4.3.9. LULC Prediction

The future LULC conditions of the Gumara watershed were predicted considering the historical change trends under two distinct scenarios. Figure 4.15 and Table 4.9 present the future LULC dynamics of the Gumara watershed in 2035 and 2065 under the BAU and GOV scenarios simulated based on the CA–Markov model.

Under the BAU scenario, consistent increases in cultivated land and settlement will occur in the watershed relative to those in the reference year (2019). Based on these results, the cultivated land area, which accounted for 1187.48 km² (83.08%) in 2019, will increase to 1240.61 km² (86.77%) and

1272.62 km² (89.01%) in 2035 and 2065, respectively (Table 4.9). In these years, cultivated land is expected to expand in the lower part adjacent to Lake Tana and in the upper part of the watershed near Debre Tabor town due to the suitability of the slope of the land surface for crop production (Figure 4.12a,b). In particular, fragmented grassland covers found in the lower part of the watershed adjacent to Lake Tana (wetland part) are highly likely to be converted to cultivated land because this area is known for its potential for rice production. Similarly, under the BAU scenario, the settlement area will increase from 2.63 km² (0.18%) in 2019 to 8.06 km² (0.56%) and 11.90 km² (0.83%) in 2035 and 2065, respectively (Table 4.9). As presented in Figure 4.15a,b, significant expansion of urban settlements in and around Debre Tabor town was predicted in the future years 2035 and 2065. Forests, shrublands, and cultivated land found near towns were the main contributors to the expansion of settlements. In contrast to the expansion of cultivated land and settlements, consistent decreases in forest, shrubland, and grassland areas will occur in the Gumara watershed relative to those in the reference year (2019). Based on the results, the BAU scenario predicts forests to be 20.53 km² (1.44%) and 15.50 km² (1.08%), shrublands to 149.5 km² (10.46%) and 119.70 (8.37%), and grasslands to be 11.12 km² (0.78%) and 10.10 km² (0.71%) in 2035 and 2065, respectively. Under this scenario, the forest and shrubland cover found near Debre Tabor town was predicted to be converted to settlement and cultivated land; only a small percentage of the forests were reserved at high elevations, while the shrubland was reserved at mid-elevation areas (Figure 4.15a,b).

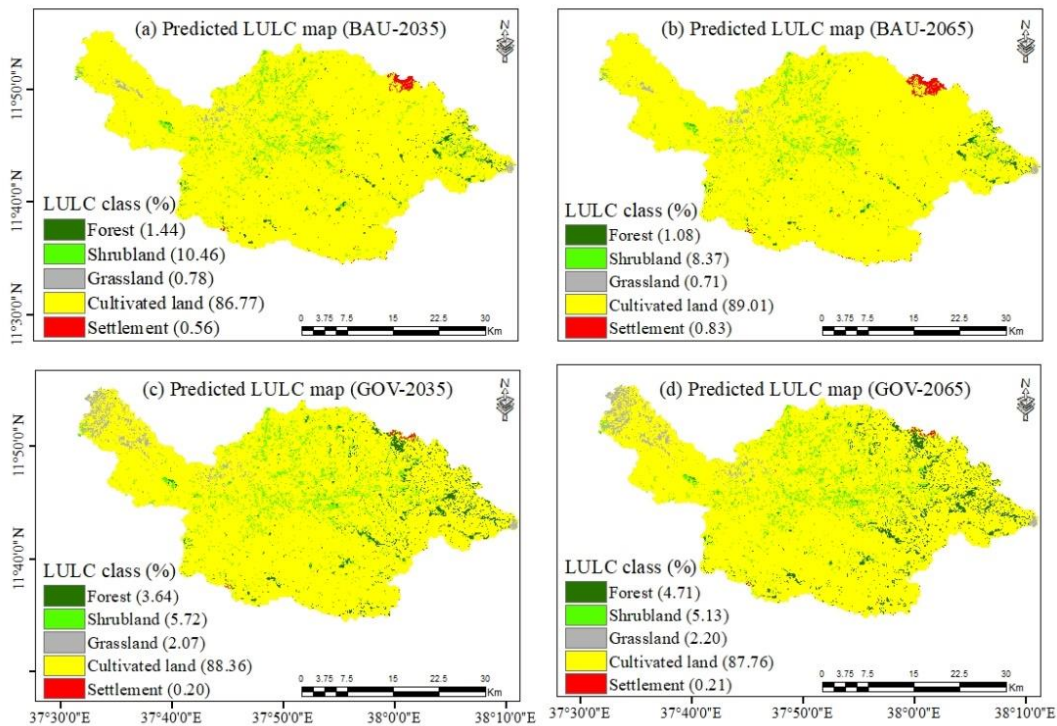


Figure 4.15. Predicted LULC maps of the Gumara watershed: (a) for 2035 and (b) for 2065 under the BAU scenario; (c) for 2035 and (d) for 2065 under the GOV scenario.

Unlike in the BAU scenario, forest and grassland are expected to increase at the expense of a decrease in cultivated land under the GOV scenario (Table 4.9). In this scenario, forest cover is expected to reach 52.05 km² (3.64%) and 67.30 km² (4.71%), and grassland cover is expected to reach 29.65 km² (2.07%) and 31.44 km² (2.2%) in 2035 and 2065, respectively. Under this scenario, shrubland will cover a smaller percentage (5.72% in 2035 and 5.12% in 2065) of the watershed due to the conversion of shrubland to forest through the implementation of afforestation programs. Under the GOV scenario, cultivated land is expected to decline slightly from 1263.44 km² (88.36%) in 2035 to 1254.86 km² (87.76%) in 2065. This scenario also promotes controlled or limited settlement expansion to reduce competition for various natural and economic resources.

Table 4.9. Predicted area and percentage of LULC classes in the Gumara watershed in 2019 and in 2035 and 2065 under the BAU and GOV scenarios.

LULC Class	Reference (2019)		BAU (2035)		BAU (2065)		GOV (2035)		GOV (2065)	
	Area (km ²)	%	Area (km ²)	%	Area (km ²)	%	Area (km ²)	%	Area (km ²)	%
Forest	37.01	2.59	20.53	1.44	15.50	1.08	52.05	3.64	67.30	4.71
Shrubland	182.81	12.79	149.50	10.46	119.70	8.37	81.74	5.72	73.28	5.13
Grassland	19.47	1.36	11.12	0.78	10.10	0.71	29.65	2.07	31.44	2.20
Cultivated land	1184.48	83.08	1236.61	86.77	1268.62	89.01	1259.44	88.36	1250.86	87.76
Settlement	2.63	0.18	8.06	0.56	11.90	0.83	2.93	0.20	2.96	0.21

4.3.10. Change Detection (2019–2065)

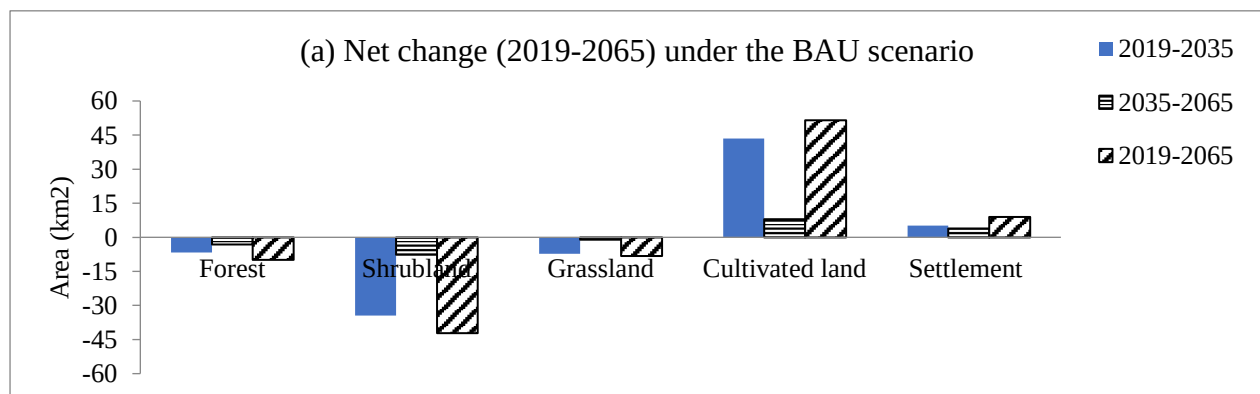
Table 4.10a,b shows the gains and losses of each LULC class in the Gumara watershed for the future periods under the two different scenarios. The results revealed contrasting changes under the different scenarios. For instance, under the BAU scenario, for the period from 2019 to 2065, cultivated land increased by 60.45 km², while forest and grassland decreased by 9.86 and 8.29 km², respectively (Table 4.10a). In contrast, for the same period, under the GOV scenario, forest and grassland increased by 42.02 and 13.01 km², respectively, while cultivated land decreased by 26.30 km² (Table 4.10b). Figure 4.16a,b also show the net change values for the future periods for different LULC classes under different scenarios. Based on the results, positive net change values of cultivated land and settlement and negative net change values of other classes were found under the BAU scenario (Figure 4.16a). For instance, net changes of 43.44, 8.00, and 3.85 km² in cultivated land and 5.14, 3.85, and 8.88 km² in settlement were found for the three periods. In contrast, under the GOV scenario, positive net change values for forestland and grassland and negative net change values for the other classes were found in the three respective periods (Figure 4.16b). For instance, the largest positive net change in forest area

was detected in the period from 2019–2065, with a value of 42.01 km², while a negative net change in forest area (loss) was detected for shrubland, with a value of –28.58 km². In general, in the BAU scenario, larger values of losses than gains (negative net change) for forest, shrubland and grassland and larger values of gains than losses (positive net changes) for cultivated land and settlement were found for the future periods (Table 4.10a, Figure 4.16a). Under the GOV scenario, larger values of gains than losses (positive net changes) for forest, shrubland and grassland and larger values of losses than gains (negative net change) for cultivated land were found for the future periods (Table 4.10b, Figure 4.16b).

Table 4.10. (a) Gains and losses of LULC classes between 2019 and 2065 under the BAU scenario. (b) Gains and losses of LULC classes between 2019 and 2065 under the GOV scenario.

(a)						
LULC	2019–2035		2035–2065		2019–2065	
	Gain	Loss	Gain	Loss	Gain	Loss
Forest	0.00	6.72	0.00	3.14	0.00	9.86
Shrubland	3.43	37.87	2.57	10.29	2.57	44.73
Grassland	0.00	7.29	0.00	1.00	0.00	8.29
Cultivated land	48.59	5.15	11.86	3.86	60.45	9.00
Settlement	5.15	0.02	3.86	0.05	9.00	0.02

(b)						
LULC	2019–2035		2035–2065		2019–2065	
	Gain	Loss	Gain	Loss	Gain	Loss
Forest	26.73	0.00	15.29	0.00	42.02	0.00
Shrubland	0.01	20.15	0.05	8.43	0.09	28.58
Grassland	11.15	0.02	1.86	0.03	13.01	0.00
Cultivated land	0.00	17.72	0.00	8.58	0.00	26.30
Settlement	0.00	0.00	0.00	0.00	0.01	0.00



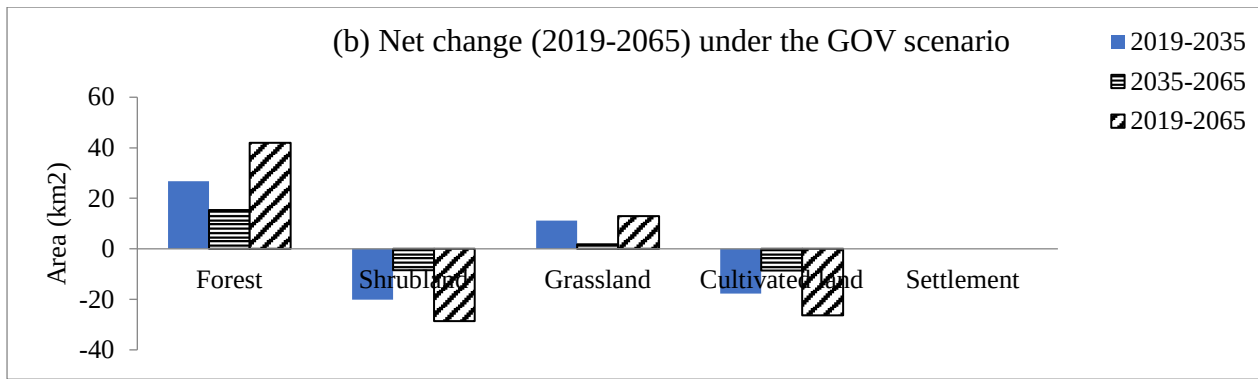


Figure 4.16. Net changes (gain-losses): (a) net change (2019–2065) under the BAU scenario and (b) net change (2019–2065) under the GOV scenario.

4.4. Discussion

4.4.1. LULC Classification and Change Detection

In this study, LULC classification was performed using the RF algorithm available in the GEE environment, and a total of five classes were identified, including forest, shrubland, grassland, cultivated land, and settlement. Based on the generated LULC maps of the four years, cultivated land covers the largest area percentage, while settlement covers the smallest. According to the classification accuracy assessment, the overall accuracies were 94.39%, 94.84%, 93.13%, and 91.13% for the years 1985, 2000, 2010, and 2019, respectively. In terms of the kappa coefficients, 0.92, 0.94, 0.90, and 0.88 were found for the four corresponding years. According to the criteria provided in (Congalton, 2001), all of the historical LULC maps showed perfect agreement, with kappa coefficient values greater than 0.81. The results of the classification accuracy assessment found in this study showed slight improvement relative to previous studies conducted in the Gumara watershed. For example, Chakilu & Moges, (2017) reported an overall accuracy of 88.33% and a kappa coefficient of 0.73 for 2013 LULC map classified using the ML classifier. These improvements in classification accuracy for this study may be due to the use of vegetation indices and topographic factors as additional variables in refining the classification. In this regard, consistently with this study, a number of studies have shown the importance of vegetation indices and topographic factors in improving LULC classification accuracy (Abida et al., 2022; Amini et al., 2022; Mananze et al., 2020).

Additionally, this study employed a random column approach to split the dataset into training (80%) and testing (20%) subsets, given its wide applicability and availability in the GEE environment. However, future studies could apply k-fold cross-validation to further improve the robustness of the classification, particularly when larger numbers of ground control points are available.

In the study watershed, significant expansion of cultivated land and settlement and declines in forest, shrubland, and grassland were observed in the historical years (1985–2019). For this, deforestation for housing and charcoal consumption, overgrazing, extensive rice cultivation and other natural and human-induced factors contributed to the decline of forests, grasslands, and shrublands (Berihun et al., 2019a; Desta et al., 2019; Regasa et al., 2021). Similarly to this study, studies conducted in the Lake Tana subbasin, where the Gumara watershed is located, have indicated the expansion of cultivated land in recent decades (Bogale, 2020; Getachew et al., 2021). Other local studies conducted in the Didessa (Tolessa et al., 2020), Andassa (Gashaw et al., 2018), Koga (Sewnet & Abebe, 2018), and Finchaa (Dibaba et al., 2020) watersheds have reported significant expansion of cultivated land and settlement areas in recent decades, which is consistent with the findings of this study.

4.4.2. Impacts of LULC Change on Socioeconomic and Environmental Conditions

In this study, LULC prediction for the years 2035 and 2065 was performed under the BAU and GOV scenarios. Under the BAU scenario, an increase in cultivated land and settlements is highly expected. More specifically, under this scenario, the expansion of cultivated land will occur in areas with gentle slopes suitable for agricultural crop production. Consistently with these findings, similar scenario-based studies have reported a significant increase in cultivated land and settlements under the BAU in future years (Hamad et al., 2018; Ruben et al., 2020; Samie et al., 2017). This significant LULC change has a number of implications for the socioeconomic and environmental conditions of the study watershed. From a socioeconomic perspective, agricultural cultivation practiced by local farmers plays an important role in ensuring food security for the local community. Local farmers can also benefit from selling vegetables, fruits, and cereal crops (for example, rice, wheat, barley, and millet) to the surrounding urban community. However, intensive agricultural cultivation has had a significant negative impact on reducing the quality of land resources and future productivity. It can also lead to excessive erosion of topsoil (fertile soil), which is crucial for agricultural production. Rapid population growth in the future could create competition for land resources and agricultural inputs (for example, fertilizers, insecticides, pesticides, improved seeds, etc.) among households. In the area, the significant conversion of grassland to cultivated land is also currently affecting indigenous cattle production (Amsalu & Addisu, 2014; Desta et al., 2019). This problem is most common in rural areas adjacent to the shore of Lake Tana (Desta et al., 2019). Other similar studies also indicated the negative consequences of intensive cultivation in reducing the economic value of livestock production (Aklile & Beyene, 2014; Mekuria et al., 2018). Furthermore, land degradation and loss of forest have negative impacts on livelihoods and poverty levels, and can lead to migration and displacements.

From an environmental perspective, if intensive agricultural cultivation continues in the future under the BAU scenario, the Gumara watershed may face serious environmental issues, such as soil erosion and degradation, deforestation, flooding, landslides, and contamination of surface and groundwater resources due to intensive use of fertilizer for cultivation, loss of biodiversity, and depletion of natural resources (Bogale, 2020; Chakilu & Moges, 2017; Wubie et al., 2016). Intensive agricultural cultivation and settlement expansions also have adverse effects on the ecosystem service values and hydrology of the studied watershed. As the study watershed is the main flow contributor to Lake Tana, sediments and contaminated surface runoff from cultivated lands pollute the lake water. Recent studies have indicated that the deterioration of the water quality of Lake Tana is the result of soil erosion and contaminant flows from the contributing watersheds (Goshu et al., 2017; Tikuye et al., 2023).

In contrast, under the GOV scenario, the expansion of cultivated land settlement areas will remain steady, and forests and other vegetation cover are expected to improve in the future. Compared to the BAU scenario, the GOV scenario is environmentally sustainable and economically profitable (Ruben et al., 2020). Environmentally, the GOV scenario can be considered sustainable, as it can reduce the adverse impact of climate change on a local or regional scale by increasing carbon sequestration and preserving biodiversity (Kassa et al., 2022). Economically, it can provide revenue for the local community from timber and nontimber products, firewood, spices, ecotourism, and medicinal plants (Beyene & Shumetie, 2023). In general, forests play a significant role in the livelihood of rural communities and can be considered a pathway for green economic growth (Kassa et al., 2022).

As indicated in several studies (Hamad et al., 2018; Samie et al., 2017), LULC dynamics are complex, and future LULC predictions are prone to uncertainty due to the uncertainty of drivers in the future. In this study, topographic, distance-to-socioeconomic development, and evidence of likelihood of change (disturbance) driver variables were considered for future LULC prediction. However, driver variables related to population density were not considered due to a lack of accurate census data. Therefore, further research can be conducted by considering these drivers when the government releases recent and reliable census data.

In this study, because the planted trees from the Green Legacy Initiative had not yet matured at the time of data collection, the areas covered by these new forests were not accounted for in the LULC prediction. However, the LULC prediction was performed using transition probability matrix and transition suitability map, allowing for transitions from other LULC classes to forest based on historical patterns. Future studies could consider incorporating the extent of forest cover after the full implementation of the GLI to improve the predictive capability of the CA–Markov model.

4.4.3. Relevance of Scenario-Based LULC Change Detection and Prediction to Policy and Practice

The scenario-based LULC change detection predictions covered in this study can provide significant input for land use policy and practice. The results of change detection under the BAU and GOV scenarios can help land use planners, policymakers, and watershed managers develop sustainable land use management plans for promoting sustainable development goals. According to the results of this study, an expansion in cultivated land and a reduction in forest and grassland over the past 34 years were observed. This could create competition for crop cultivation and livestock grazing among households. To handle such competition for land resources, introducing a more integrated sustainable land resource management policy that accounts for the socioeconomic values of crop and livestock production is recommended (Cochrane & Hadis, 2019; Mekuria et al., 2018). In this regard, the government and other stakeholders should work to combat excessive land resource utilization and rapid population growth to ensure the food security of local farmers (Agidew & Singh, 2017). Stakeholders should also work cooperatively to address issues related to land tenure security, land use rights, and land certification. Furthermore, to reduce the adverse effects of land use change on the environment, stakeholders should encourage communities to participate in the GLI program. It is also recommended that various land management practices, such as agroforestry, polyculture, crop rotation, and smart agriculture, be implemented to increase the economic productivity and environmental sustainability of the GLI program.

4.5. Conclusions

Long-term LULC change detection and prediction studies are crucial for providing significant information on the current and future hydrological conditions of watersheds and large river basins. For this reason, this study focused on change detection and prediction of LULC in the Gumara watershed using the cloud-based platform Google Earth Engine (GEE) and the geospatial prediction model cellular automata–Markov (CA–Markov). The first part of the study focused on LULC classification and change detection in historical periods. For LULC classification, Landsat-5/OLI and 8/TM images from 1985, 2000, 2010, and 2019 were used as inputs for the RF classification algorithm built into the GEE environment. To improve the classification accuracy and distinguishability of complex classes, other variables, such as vegetation indices (NDVI and SAVI) and topographic factors (elevation and slope), were used as inputs for the RF classifier. Using this cloud-based image classification approach, five major LULC classes, namely, forest, shrubland, grassland, cultivated land, and settlements, were identified for the study watershed. The results of the change analysis for the four historical periods (1985–2000, 200–2010, 2010–2019, and 1985–2019) revealed significant LULC changes in the study

watershed. Over the past 34 years (1985–2019), expansions of cultivated land and settlements and decreases in forest, shrubland, and grassland were detected due to increasing anthropogenic disturbances. From the analysis, a significant increase in cultivated land from 58.60 to 83.08% and a decrease in forest from 5.22 to 2.59% were detected between 1985 and 2019.

In the second part of this study, future LULC maps of the Gumara watershed were generated for the years 2035 and 2065 using the CA–Markov model available in the land change modeler (LCM) module of IDRISI Selva 17.0. To predict future LULC maps, earlier and later images, the Markovian transition probability matrix (TPM), and transition suitability maps (TSMs) were used as inputs for the CA–Markov model. To generate the TSMs, a multilayer perceptron (MLP) artificial neural network (ANN) algorithm was employed for this study. Two LULC scenarios, namely, the business-as-usual (BAU) and governance (GOV), were considered. For the first scenario (BAU), the most dominant LULC TSMs were generated based on the current trend of LULC change using six LULC driver variables, such as elevation, slope, distance from streams, distance from roads, distance from towns, and evidence likelihood. Under this scenario, significant expansions of cultivated land and settlements were predicted for the years 2035 and 2065 due to human-induced anthropogenic disturbances. Therefore, cultivated land and settlements are expected to increase from 83.08 to 89.01% and 0.18 to 0.21%, respectively, between 2019 and 2065.

On the other hand, the GOV scenario considers the Green Legacy Initiative program, which is currently under implementation. For this scenario, topographic factors (slope and elevation) were considered to generate TSMs. Under this scenario, forest and grassland areas are expected to increase from 2.59% in 2019 to 4.71% in 2065 due to the implementation of afforestation and reforestation programs and controlled anthropogenic disturbances. Overall, the scenario-based findings of this study can provide information for government policymakers, land use planners, and watershed managers to developing sustainable land management policies.

In this study, LULC classification was performed using spectral bands, vegetation indices, and topographic factors as inputs for the RF algorithm. In this regard, further research can be performed by considering texture information following recent studies (Cuypers et al., 2023; Shafizadeh-Moghadam et al., 2021). In this study, future LULC prediction was performed considering topographic and proximity-related factors. Hence, future predictions of LULC maps can also be further researched by considering population density data when the government releases accurate and updated census data. Moreover, further studies could be performed by studying the impacts of LULC on the hydrology and ecosystem service values of the studied watershed.

CHAPTER 5

5. Identifying Flood Source Areas and Analyzing High-Flow Extremes under Changing Land Use/Land Cover, and Climate in the Gumara Watershed, Upper Blue Nile Basin, Ethiopia

This chapter has been published as:

Belay, H., Melesse, A. M., Tegegne, G., & Tamiru, H. (2025). Identifying Flood Source Areas and Analyzing High-Flow Extremes Under Changing Land Use, Land Cover, and Climate in the Gumara Watershed, Upper Blue Nile Basin, Ethiopia. Climate, 13(1), 7. <https://doi.org/10.3390/cli13010007>

Abstract

Changes in land use and land cover (LULC) and climate increasingly influence flood occurrences in the Gumara watershed, located in the Upper Blue Nile (UBN) basin of Ethiopia. This study assesses how these factors impact return period-based peak floods, flood source areas, and future high-flow extremes. Merged rainfall data (1981–2019) and ensemble means of four CMIP5 and four CMIP6 models were used for historical (1981–2005), near-future (2031–2055), and far-future (2056–2080) periods under representative concentration pathways (RCP4.5 and RCP8.5) and shared socioeconomic pathways (SSP2-4.5 and SSP5-8.5). Historical LULC data for the years 1985, 2000, 2010, and 2019 and projected LULC data under business-as-usual (BAU) and governance (GOV) scenarios for the years 2035 and 2065 were used along with rainfall data to analyze flood peaks. Flood simulation was

performed using a calibrated Hydrologic Engineering Center–Hydrologic Modeling System (HEC-HMS) model. The unit flood response (UFR) approach ranked eight subwatersheds (W1–W8) by their contribution to peak flood magnitude at the main outlet, while flow duration curves (FDCs) of annual maximum (AM) flow series were used to analyze changes in high-flow extremes. For the observation period, maximum peak flood values of 211.7, 278.5, 359.5, 416.7, and 452.7 m³/s were estimated for 5-, 10-, 25-, 50-, and 100-year return periods, respectively, under the 2019 LULC condition. During this period, subwatersheds W4 and W6 were identified as major flood contributors with high flood index values. These findings highlight the need to prioritize these subwatersheds for targeted interventions to mitigate downstream flooding. In the future period, the highest flow is expected under the SSP5-8.5 (2056–2080) climate scenario combined with the BAU-2065 land use scenario. These findings underscore the importance of strategic land management and climate adaptation measures to reduce future flood risks. The methodology developed in this study, particularly the application of RF-MERGE data in flood studies, offers valuable insights into the existing knowledge base on flood modeling.

Keywords: climate change; land use and land cover change; flood source area identification; Gumara watershed; HEC-HMS; high-flow extremes

5.1. Introduction

Recently, flooding has become the most common and leading environmental hazard, with diverse impacts on human life, property, socioeconomic development, and agricultural production (Nel et al., 2014; Shah et al., 2017). It is aggravated mostly by factors such as land use and land cover (LULC) and climate changes (Irannezhad et al., 2018; Mzava et al., 2021). LULC changes such as deforestation, agricultural expansion, and urbanization result in an increase in surface runoff by changes in the hydrologic characteristics of basins and watersheds (Cuo, 2016; Kundu & Olang, 2011), while climate change causes flooding by changing the frequency, magnitude, and duration of extreme rainfall events (Kim et al., 2021; Meresa et al., 2022; Yan et al., 2016).

For projecting extreme rainfall events that would cause flooding, general circulation models (GCMs) available in the Coupled Model Intercomparison Project Phases 5 and 6 (CMIP5 and CMIP6) play a significant role (Almazroui et al., 2021; Taylor et al., 2012). However, these models are often associated with biases due to their coarse spatial resolution (Gebrechorkos et al., 2023). To address this issue, the use of high-resolution downscaled outputs, such as those from the NASA Earth Exchange-Global Daily Downscaled Projections (NEX-GDDP) dataset, is generally recommended (Melton, 2015; Thrasher et al., 2022). The NASA NEX-GDDP-CMIP5 and CMIP6 datasets provide

daily temporal resolution and a spatial resolution of 0.25° (approximately $25 \text{ km} \times 25 \text{ km}$), making them suitable for watershed- and basin-scale studies (Jose & Dwarakish, 2022; Sharma & Kale, 2022). Furthermore, the biases associated with climate models can be mitigated by evaluating and selecting the best-performing models, applying bias correction techniques, and using multi-model ensemble means of bias-corrected models (Jose et al., 2022; Raju & Kumar, 2020; Wang et al., 2022).

Historical LULC maps generated from remotely sensed images have been extensively used to assess past watershed and basin conditions (Getachew & Manjunatha, 2022; Irannezhad et al., 2018; Mewded et al., 2021; Miller & Hutchins, 2017). Additionally, projected LULC maps under different scenarios are crucial for understanding future conditions. Consequently, several studies have focused on LULC predictions in different regions (Faichia et al., 2020; Halmy et al., 2015; Liping et al., 2018). For example, in the Gumara watershed, Belay et al. (2024b) projected future LULC changes under a business-as-usual (BAU) scenario and a governance (GOV) scenario. The BAU scenario assumes the continuation of current trends in land use change and socioeconomic development, whereas the GOV scenario incorporates the Green Legacy Initiative (GLI), a program currently being implemented by the Ethiopian government. Their study revealed significant expansion in cultivated land and settlements under the BAU scenario, whereas the GOV scenario predicted increases in forest, shrubland, and grassland. Similarly, a study by Gebresellase et al. (2023) in the upper Awash basin of Ethiopia reported the expansion of agricultural lands and urban settlements under the BAU scenario and improvements in forest cover under the GOV scenario.

Flood occurrence can be studied by estimating peak floods for different return periods. This is a crucial aspect in designing safe and cost-effective flood protection structures to minimize the destructive impacts of flooding on the environment (Baky et al., 2020; Emam et al., 2016; Tegegne et al., 2020). Return period-based peak floods can be estimated using statistical flood frequency analysis and hydrological rainfall–runoff models. The traditional statistical flood frequency analysis involves estimation of flood quantiles via a best-fitting probability distribution on the basis of the assumption that historical discharge time series are stationary and independent (Hosking & Wallis, 1997). However, rainfall–runoff hydrological models simulate the transformation of design storms (rainfall) into design floods, taking into account the effects of changing LULC and climate (Mareuil et al., 2007; Noori et al., 2016; Yisehak, 2021).

Flooding mostly occurs at certain downstream reaches of the main river. Hence, before flood control structures are constructed, quantifying the contribution of upstream subwatersheds to the peak flood magnitude at the main outlet of the watershed is often recommended. This method is commonly known as flood source area identification (FSAI) (Saghafian & Khosroshahi, 2005). FSAI can be performed

via multicriteria evaluation (MCE) and the unit flood response (UFR) approach (A. Singh et al., 2021). The MCE approach can be implemented via a geographic information system (GIS), which considers the linear combination of the weights of several flood control factors (Argaz et al., 2019; Elkhachy, 2015). However, this approach does not account for flow routing through rivers. The second approach, UFR, can be performed via hydrological models by accounting for flood routing through rivers for watersheds with diverse conditions (Singh et al., 2021). This method was first applied to the Damavand watershed in Iran by Saghafian and Khosroshahi (2005) and has since been used in various watersheds. For example, Abdulkareem et al. (2018) employed the UFR approach to assess the impact of LULC changes on FSAI for the Kelantan basin in Malaysia. In their study, the authors employed the Hydrologic Engineering Center–Hydrologic Modeling System (HEC-HMS) model and stated its importance for ranking subwatershed units on the basis of their contribution to peak discharge at the main outlet. Similarly, Fiorillo & Tarchiani (2017) applied this approach to a catchment in Niger and reported its suitability for identifying flood source areas.

Several studies conducted across various basins and watersheds have demonstrated a potential increase in high-flow extremes in future periods. These studies typically employed hydrological models to simulate future streamflow based on GCM outputs. For instance, Yang et al. (2022) assessed future changes in high-flow extremes in the Jiulong River Basin of Southeast China by simulating streamflow under changing LULC and climate conditions. Their findings indicated an increase in high-flow extremes due to intensified extreme rainfall and LULC changes driven by human activities. Similarly, Mahato et al. (2022) showed an increase in flood frequency in the Brahmani River basin, India, by simulating streamflow using a semi-distributed hydrological model driven by outputs from CMIP6 models. In the Ethiopian context, Kassaye et al. (2024) showed a projected increase in high-flow extremes in the Baro River Basin by simulating streamflow using six GCMs under different scenarios. Likewise, Yalcin (2024) indicated a projected rise in flood frequency in Bitlis Creek, Turkey.

The downstream area of the Gumara watershed, particularly near Lake Tana, is one of the most flood-affected regions in the Upper Blue Nile (UBN) basin of Ethiopia (Alemu & Assaye, 2020). Several studies have addressed flood risk in this area through different approaches, including flood hazard mapping using the MCE method (Gashaw & Legesse, 2011), statistical flood frequency analysis (Tegegne et al., 2020), hydraulic flood inundation modeling (Nigusie et al., 2021), and flood mapping via Sentinel-1 images (Melkamu et al., 2022). However, return period-based peak flood estimation, FSAI, and extreme flow estimations under varying LULC and climate scenarios remain underexplored in the upstream region of the watershed. Additionally, most flood simulation studies in the Gumara watershed have relied on ground-based rainfall data. However, these observations often contain

uncertainties due to missing data, sparse rain gauge networks, and the influence of topography (Belay et al., 2022; Molini et al., 2005). To overcome these limitations, recent studies (Baez-Villanueva et al., 2020; Mekonnen et al., 2022; Min et al., 2020) have suggested merging ground-based rainfall data with gridded rainfall products (GRFPs). This approach enhances the accuracy of flood simulations by reducing the uncertainties of ground-based rainfall measurements.

Hence, the objectives of this study are to (1) examine the impact of LULC change on return period-based peak floods and flood source areas (FSA) for the observation period (1981–2019) and (2) assess the combined impacts of LULC and climate change on high-flow extremes, considering historical (1981–2005), near-future (2031–2055), and far-future (2056–2080) periods. To achieve these objectives, flood simulations were performed using a calibrated and validated HEC-HMS model.

For the observation period, the study utilized merged rainfall estimates from ground-based observed rainfall and three gridded rainfall products (GRFPs): Multi-Source Weighted-Ensemble Precipitation (MSWEP) (Beck et al., 2017), Climate Hazards Group InfraRed Precipitation with Stations (CHIRPS) (Funk et al., 2015), and the Enhanced Global Dataset for the Land Component of the Fifth Generation of European Reanalysis (ERA5-Land) (Muñoz-Sabater et al., 2021). The merging process was performed using a random forest merging algorithm (RF-MERGE). LULC maps for the years 1985, 2000, 2010, and 2019 were incorporated alongside these merged rainfall estimates for this period.

To assess changes in high-flow extremes between historical and future periods under changing LULC and climate conditions, high flow simulations were conducted using bias-corrected ensemble means of historical and projected rainfall data from four CMIP5 and four CMIP6 models. For the projected rainfall, the study accounted for representative concentration pathways (RCP4.5 and RCP8.5) for CMIP5 models and shared socioeconomic pathways (SSP2-4.5 and SSP5-8.5) for CMIP6 models. Additionally, future LULC scenarios under the BAU and GOV scenarios for 2035 and 2065 were considered for the near-future and far-future periods, respectively, alongside the future climate scenarios.

In summary, this study offers valuable insights into prioritizing flood source areas in the Gumara watershed and proposes targeted runoff reduction mechanisms. The estimation of high-flow extremes provides critical input for developing effective flood risk protection strategies, while the study's methodology serves as a framework for flood simulations in similar watersheds across the UBN basin and beyond.

5.2. Materials and Methods

5.2.1. Study area

The Gumara watershed is part of the Lake Tana subbasin, which is located in the UBN basin of Ethiopia (Figure 5.1). The watershed is primarily drained by the Gumara River, which originates from Guna Mountain. Geographically, it spans from 11°35' N to 11°55' N latitude and from 37°35' E to 38°15' E longitude. The drainage area of the watershed is approximately 1256.7 km² it is main flow contributor to the Lake Tana (Negatu et al., 2022). The topography of the watershed is diverse, with elevations ranging from 1792 to 3708 m above mean sea level (amsl) (Figure 5.1c). It is characterized by steep gradients and mountainous terrain in its upstream areas and flat downstream floodplains. The watershed experiences a unimodal rainfall pattern, with the main rainy season occurring from June to September. The watershed receives an average annual rainfall of 1445 mm, and its average annual temperature is about 20.5 °C (Chakilu et al., 2020). LULC in the watershed is dominated by cultivated land, which accounts for more than 80% of the total area, while the remaining portion of the watershed comprises forest, shrubland, grassland, and settlement areas (Belay et al., 2024b). The predominant soil texture classes in the region include clay, clay loam, sandy clay, silty clay, and silty clay loam (Melkamu et al., 2022). The majority of the watershed is characterized by scattered rural settlements, where the local livelihood is primarily based on a mixed farming system (crop cultivation and livestock raising) (Wubie et al., 2016). The downstream part of the watershed, which is adjacent to Lake Tana, is susceptible to frequent flood events due to high runoff generated from the upland watershed (Dawit et al., 2019; Gashaw & Legesse, 2011).

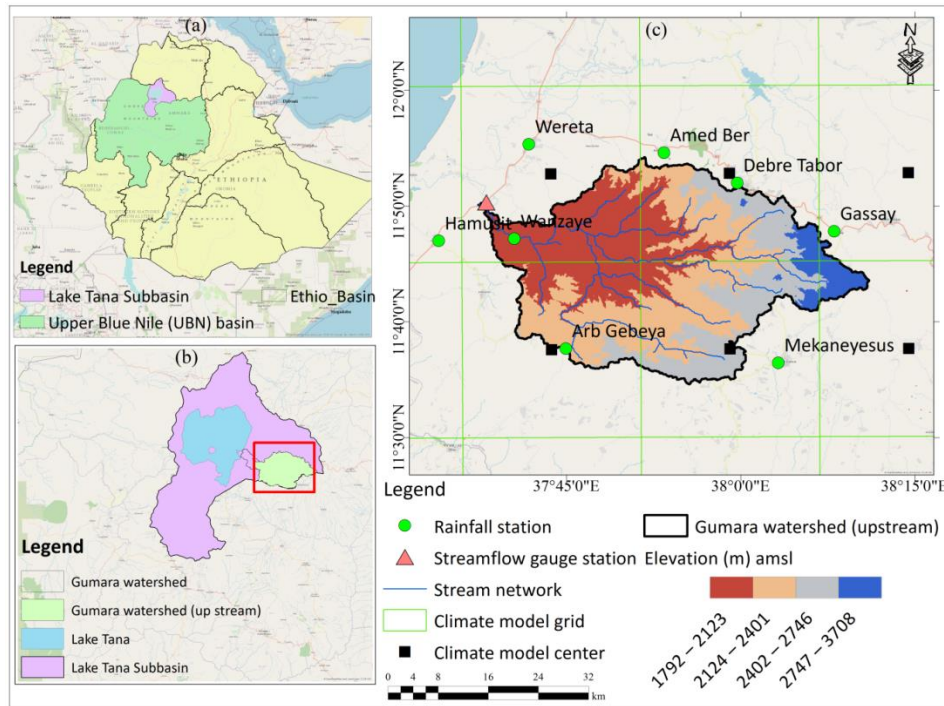


Figure 5.1. Location map of the study area. (a) Location map of the Upper Blue Nile (UBN) basin within the 12 river basins of Ethiopia. (b) Location map of the upstream Gumara watershed (bounded by a red rectangle) within the Lake Tana subbasin, and (c) Detailed map showing the rainfall and streamflow gauging stations, stream network, climate model grid (25 km × 25 km), and grid center for the NASA dataset, and elevation map of the upstream (flood source area) part of the Gumara watershed.

5.2.2. Data Used

For this study, various spatial and temporal data were collected from different sources. These include observed ground-based rainfall and streamflow, gridded rainfall products, climate model data, and spatial data such as elevation, soil, and LULC data.

5.2.2.1. Observed Rainfall and Streamflow Data

Ground-based daily rainfall data from eight meteorological stations located in and around the Gumara watershed were collected from the National Meteorological Agency (NMA) of Ethiopia, covering the long-term observation period from 1981 to 2019 (Table 5.1).

The observed daily streamflow time series data (1981–2019) for the Gumara River at the Wanzaye gauging station were obtained from the Ministry of Water, Irrigation, and Electricity (MoIR) of Ethiopia. Selected events from this dataset were utilized for hydrological model sensitivity analysis, calibration, and validation.

Table 5.1. Location and elevation information of the eight ground-based meteorological stations located in and around the Gumara watershed.

Station Name	Latitude (°)	Longitude (°)	Elevation (m)
Amed Ber	11.91	37.88	2051
Arb Gebeya	11.62	37.74	2248
Debre Tabor	11.87	38.01	2612
Gassay	11.79	38.13	2789
Hamusit	11.78	37.56	1954
Mekaneyesus	11.58	37.90	2374
Wanzaye	11.78	37.68	1821
Wereta	11.92	37.70	1819

5.2.2.2. Gridded rainfall products (GRFPs)

In watersheds with diverse topographies, such as the Gumara watershed, sparsely distributed meteorological stations may not adequately capture rainfall characteristics. To address this issue, three GRFPs were accessed and merged with ground-based observed rainfall. The three GRFPs selected for this study were MSWEP, CHIRPS, and ERA5-Land. Detailed descriptions of these GRFPs are provided in Chapter 2.

5.2.2.3. General Circulation Models (GCMs)

Historical (1981–2005), near-future (2031–2055), and far-future (2056–2080) rainfall data from four selected CMIP5 and four CMIP6 models were accessed from the NASA NEX-GDDP dataset. For the CMIP5 models, future scenarios considered were RCP4.5 and RCP8.5, while for the CMIP6 models, SSP2-4.5 and SSP5-8.5 were utilized. The models were chosen on the basis of their better performance in reproducing historical extreme rainfall in the UBN basin following our recent work (Belay et al., 2024a). All the CMIP5 and CMIP6 models are statistically downscaled outputs with a daily temporal resolution and 25 km × 25 km spatial resolution. Table 5.2 summarizes detailed descriptions, including the resolutions of the climate models, modeling centers, and countries of the selected climate models. Details on the comparison and evaluation of the performance of the CMIP5 and CMIP6 models can be found in Belay et al. (2024a).

Table 5.2. Descriptions of the NASA NEX-GDDP dataset (CMIP5 and CMIP6 climate models) used in this study.

GCM	Name	Spatial Resolution (km)	Modeling Center	Country
CMIP5	MIROC5	25 km × 25 km	National Institute for Environmental Studies, the University of Tokyo	Japan
	MRI-CGCM3	25 km × 25 km	Meteorological Research Institute	Japan
	CanESM2	25 km × 25 km	Canadian Centre for Climate Modeling and Analysis	Canada

	MPI-ESM1-2-LR	25 km × 25 km	Max Planck Institute for Meteorology	Germany
	MPI-ESM1-2-LR	25 km × 25 km	Max Planck Institute for Meteorology	Germany
	MRI-ESM2-0	25 km × 25 km	Meteorological Research Institute	Japan
CMIP6	CNRM-CM6-1	25 km × 25 km	Centre National de Recherches Meteorologiques	France
	BCC-CSM2-MR	25 km × 25 km	Beijing Climate Center, China Meteorological Administration	China

5.2.2.4. Elevation, Soil, and LULC Data

The elevation data of the study watershed were extracted from a 30 m spatial resolution digital elevation model (DEM) of the Shuttle Radar Topography Mission (SRTM) (Farr et al., 2007). The SRTM DEM data was accessed from USGS Earth Explorer via this link: <https://earthexplorer.usgs.gov/>. The data was primarily used to generate subwatershed units and other watershed characteristics, including watershed slope and stream network.

Hydrologic Soil Groups (HSGs) for the study area were extracted from a 250 m spatial-resolution soil grid map established by the USDA. The data was accessed via this link: https://daac.ornl.gov/cgi-bin/dsviewer.pl?ds_id=1566. As shown in Figure 5.2c, HSG-D (clay loam, sandy clay, silty clay, silty clay loam, or clay) covers approximately 89% of the study watershed. These soils have high runoff potential because of very slow infiltration rates (Ross et al., 2018). The remaining portion of the study watershed is covered by HSG-C (sandy clay loam). These soils have a moderately high runoff potential due to slow infiltration rates (Ross et al., 2018).

Raster files of historical and future LULC maps of the Gumara watershed, with a 30 m spatial resolution, were clipped from our previous work (Belay et al., 2024b), which accounted for the entire Gumara watershed. In that work (Belay et al., 2024b), the LULC maps were generated using composite images from Landsat-5/Thematic Mapper (TM) for the years 1985, 2000, and 2010, and Landsat-8/Operational Land Imager (OLI) for the year 2019. For these years, cloud-free images from January to March were accessed from the U.S. Geological Survey via the GEE data catalog. LULC classification was performed using a random forest (RF) algorithm (Breiman, 2001) in the GEE environment, resulting in the identification of five dominant classes: forest, shrubland, grassland, cultivated land, and settlement areas, which describe the land use conditions of the study watershed.

In our previous work (Belay et al., 2024b), future land use prediction was performed via the Cellular Automata-Markov (CA-Markov) model available in the land change modeler (LCM) module of IDRISI Selva 17.0 (Eastman, 2009). For the prediction, historical LULC maps (baseline) and various land-use change driver variables were considered, including elevation, slope, distance from roads, distance from streams, distance from towns, and socio-economic development (evidence of the likelihood of change). The prediction was conducted under two “what-if” scenarios: the business-as-

usual (BAU) scenario and the governance (GOV) scenario. The BAU scenario considered the current trend of land use conversion and change drivers (transition probability), whereas the GOV scenario accounted for the massive tree seedling plantation program of the Ethiopian government, known as the Green Legacy Initiative (GLI) program (Beyene & Shumetie, 2023). Figure 5.2d–k show historical and predicted LULC maps of the Gumara watershed. Details on methods used for classification, accuracy assessment, LULC change drivers, scenario-based LULC prediction, and change detection for the entire Gumara watershed can be found in Belay et al. (2024b).

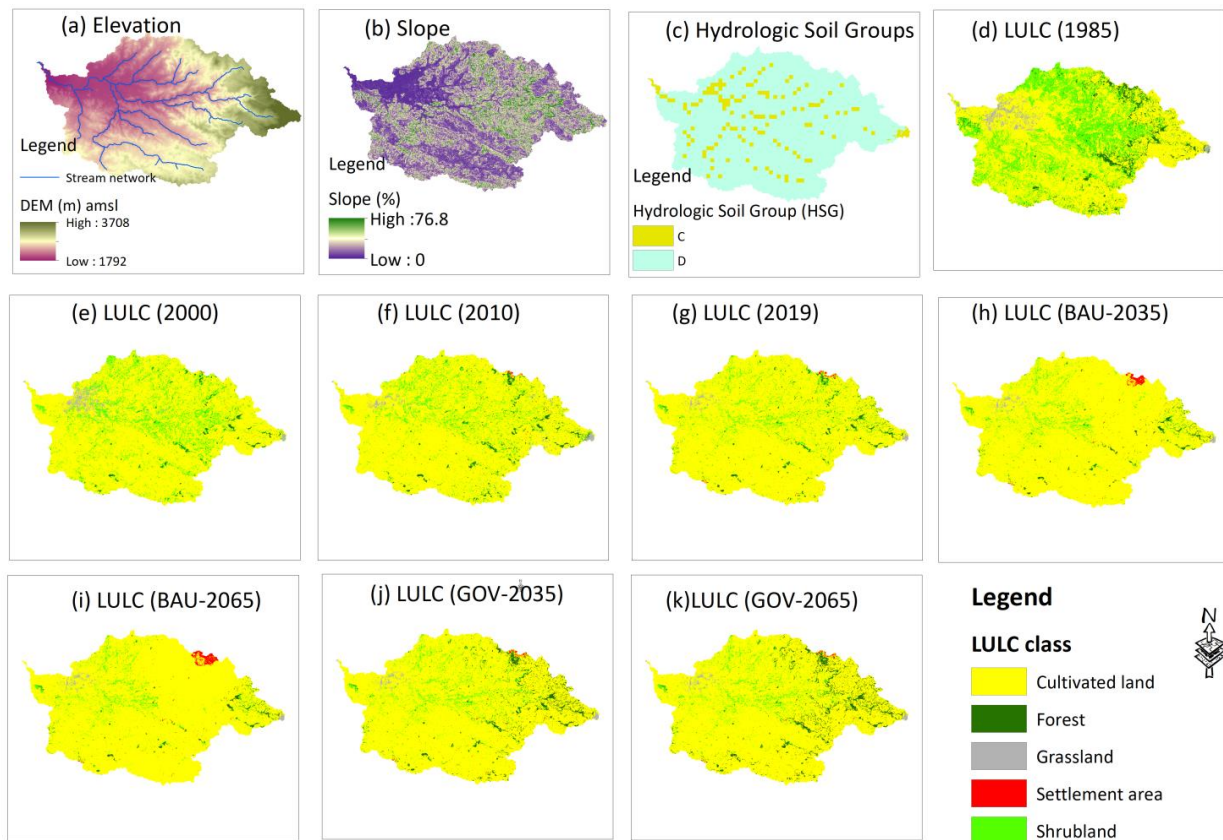


Figure 5. 2. Elevation, slope, hydrologic soil groups, and historical and projected land use and land cover maps of the Gumara watershed for the historical and future periods.

5.2.3. Methods

This study analyzed peak floods for different return periods (5-, 10-, 25-, 50-, and 100-year) and flood source areas during the observation period (1981–2019) under varying LULC conditions. Additionally, high-flow extremes were assessed for historical (1981–2005) and future (2031–2080) periods under different LULC and climate scenarios. The analysis involved collecting and processing spatiotemporal data, including daily ground-based rainfall, streamflow, GRFPs (MSWEP, CHIRPS, and ERA5-Land), CMIP5 and CMIP6 models, elevation, LULC, and soil data.

Ground-based rainfall data were merged with the three GRFPs using the RF-MERGE algorithm (Breiman, 2001) to enhance data accuracy. The merging process included four main steps: input data preparation, setting up the RF model, training the RF model, and performing the merging (prediction). For merging, ground-based rainfall data were used as the dependent variable, while GRFPs and other auxiliary data were used as independent variables. The resulting merged rainfall product was subsequently utilized in rainfall–runoff modeling for extracting annual maximum (AM) 1-day rainfall series, and for correcting biases in climate model outputs. In the study, rainfall data from CMIP5 (MIROC5, MRI-CGCM3, CanESM2, and MPI-ESM1-2-LR) and CMIP6 (MPI-ESM1-2-LR, MRI-ESM2-0, CNRM-CM6-1, and BCC-CSM2-MR) models were also bias corrected, and their ensemble means were predicted for historical and future periods to reduce uncertainties associated with climate models. Bias correction was performed using the quantile mapping (QM) method (Déqué, 2007). From the corrected daily rainfall data, AM 1-day rainfall series were extracted and subsequently used to estimate high-flow extremes in the near-future and far-future periods.

Flood simulation was conducted using the HEC-HMS model (version 4.11) (USACE, 2008). The process included subwatershed delineation, entering rainfall data, model selection, parameter estimation and sensitivity analysis, calibration and validation, and flood simulation under various climate and LULC scenarios. Using the calibrated model, peak floods for different return periods were determined, flood source areas prioritized, and high-flow extremes for historical and future periods assessed. The overall methodology is outlined in Figure 5.3, with detailed explanations in subsequent sections.

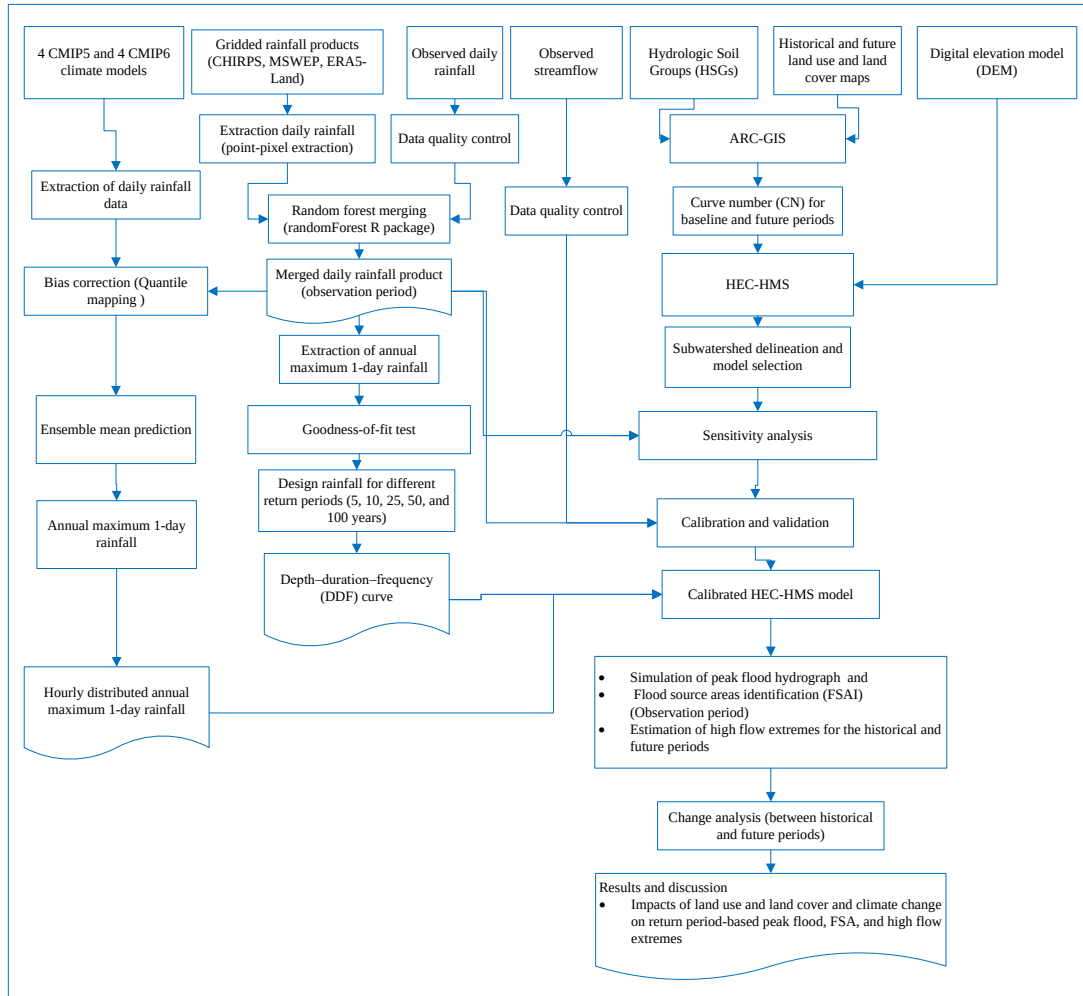


Figure 5. 3. Methodological framework of the study.

5.2.4. Data Quality Control

In hydroclimatic studies, the use of long-term, homogeneous, and consistent data is generally recommended. However, the ground-based stations considered in this study have missing rainfall data and short-term rainfall records at the Hamusit, Wanzaye, and Arb Gebeya stations. The missing data were filled via the inverse distance weighting (IDW) technique, whereas short-term rainfall records were extended via the maintenance of variance extension, type 1 (MOVE.1) technique (Hirsch, 1982). After filling in missing data and extending short-term data, a homogeneity test was employed to detect change points in the mean annual rainfall data via the nonparametric Pettitt test (Pettitt, 1979). Similarly, change in the average streamflow of the Gumara River was assessed using the Pettitt test, and no significant shift in streamflow was detected.

Double-mass curve (DMC) analysis was also employed to check the consistency of the mean annual rainfall data. This analysis involved inspecting significant changes in slope by plotting the cumulative mean annual rainfall of all stations on the x -axis and the cumulative mean annual rainfall of each station

on the y-axis. From the analysis, all the stations were found to be consistent (Figure 5.4a), since no significant changes in slope were detected in the DMC plot. Figure 5.4b–d also present mean annual rainfall at each ground-based station, mean monthly rainfall, and mean monthly discharge data, respectively.

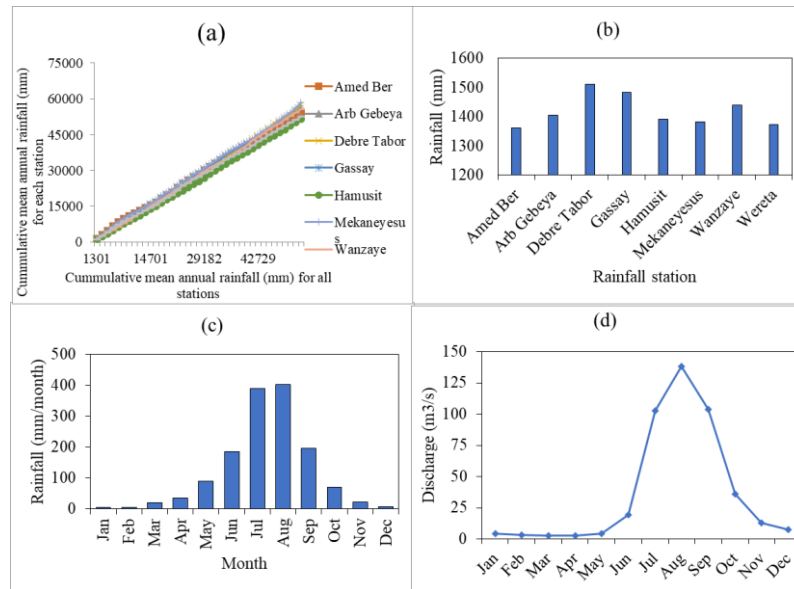


Figure 5.4. Observed ground-based rainfall and discharge data from 1981 to 2019 for the Gumara watershed. (a) Double mass curve analysis, (b) mean annual rainfall of each ground-based rainfall station, (c) mean monthly rainfall, and (d) mean monthly discharge.

5.2.5. Random Forest Merging (RF-MERGE)

To improve the quality of the rainfall data, the random forest (RF) merging approach (RF-MERGE) was employed to combine daily ground-based observed rainfall with three GRFPs (MSWEP, CHIRPS, and ERA5-Land). RF is a supervised machine learning algorithm that can be used for both classification and regression (Breiman, 2001). Among the various merging approaches, RF-MERGE was selected based on our previous work (Belay et al., 2024a), conducted in the study region. In that study, RF-MERGE demonstrated the best performance in reproducing observed rainfall compared to individual GRFPs and other merging approaches, as evaluated by both statistical and categorical performance measures. Additionally, RF-MERGE requires a minimal number of model parameters and is capable of handling high-dimensional data (Baez-Villanueva et al., 2020).

For the merging process, ground-based rainfall data, three GRFPs, and auxiliary data (including date, month, year, and elevation) were first prepared. Next, the RF model was set up to map the relationship between the dependent and independent variables. In this study, ground-based rainfall data served as the dependent variable, while the three GRFPs, along with the auxiliary data, were used as independent

variables. During training, the RF model learned the relationship between the dependent and independent variables. Based on this, the optimal parameter values of the RF algorithm, such as the number of trees (N_t), the minimum number of bootstrap samples (N_{min}), and the number of features (N_f) at the splitting node, were estimated. Finally, using the trained RF model, rainfall was predicted at stations located in and around the Gumara watershed (Table 5.2). The merging procedure was performed via the “randomForest” R package version 4.7 (Breiman, 2018). The analysis yielded estimated parameter values of 200, 6, and 3 for N_t , N_{min} , and N_f , respectively. These parameters were determined through trial-and-error procedures and by comparison with parameters estimated in previous studies (Fan et al., 2021; Nguyen et al., 2021). Using these parameters, the trained model was subsequently used to predict daily rainfall at the eight testing stations. The merged rainfall data were then used to extract the AM 1-day rainfall, correct the bias of the climate models, and calibrate/validate the hydrological model. A comprehensive review, including assumptions, procedures, and limitations of various merging approaches, such as RF-MERGE, can be found in our previous work (Belay et al., 2022).

5.2.6. Design Rainfall and Depth–Duration–Frequency (DDF) Curve

In this study, the annual maximum 1-day rainfall data series for the observation period (1981–2019) was extracted and fitted to commonly used probability distributions: normal (NOR), lognormal (LN3), gamma (GAM), Gumbel (GUM), Pearson type III (PE3), log Pearson type III (LPE3), and generalized extreme value (GEV) distributions. The parameters of these distributions were calculated via the L-moments method provided in Hosking & Wallis (1997). The Anderson–Darling (AD) test (Anderson & Darling, 1952) was employed to assess goodness of fit by comparing the CDFs of the observed data with those of the candidate distributions. This test is sensitive to deviations in the tails of the probability distribution, making it valuable for applications involving extreme values (Stephens, 1974). The best-fit distribution was selected on the basis of the lowest AD statistic (A^2) at the 5% significance level and used for estimating design rainfall for different return periods.

To simulate flood hydrographs for different return periods (5-, 10-, 25-, 50- and 100-year), a short-duration (example with an hourly distribution) depth–duration–frequency (DDF) curve is often needed. For this, a short-duration hourly distributed DDF curve was developed using the following equation:

$$R_t = R_{24} \left(\frac{t}{24} \right) \left(\frac{b+24}{b+t} \right)^n \quad (5.1)$$

where R_t is the computed rainfall depth for a duration of t hours, R_{24} is the design rainfall depth for a 24-h (1-day) duration, t is the rainfall duration in hours, b is a parameter that controls the relationship between different durations and can be determined on the basis of regional studies, and n is an exponent that adjusts the amount at which rainfall decreases with shorter durations and can be determined empirically on the basis of regional studies. For this study, the DDF curve for a 1-h duration was developed using 0.3 for the parameter b and 0.9 for the exponent n following regional studies conducted in Ethiopia (Bibi, 2023; Zinabie & Kebede, 2020).

5.2.7. Bias Correction

It is common for climate model simulations to exhibit bias (uncertainties) due to their coarse spatial resolution, model assumptions, boundary conditions, spatial averaging, and other factors (Acharya et al., 2013; Kaur & Kaur, 2023). To address this issue, it is generally recommended that biases in climate models be corrected before their outputs are applied in impact assessment studies (Yamamoto et al., 2021). Among the different types of bias correction methods, the QM approach was used in this study because of its better performance in the study region (Belay et al., 2024a). The QM method uses the quantile–quantile relationship to match the distribution function of climate model simulations with observed data (Déqué, 2007). The method assumes that the cumulative distribution functions (CDFs) of the observed and simulated datasets can be matched, meaning that the CDFs of the observed and simulated data should be similar enough for meaningful bias correction (Enayati et al., 2021). Based on this assumption, for a given simulated value x_{sim} , QM bias correction adjusts it using:

$$x_{cor} = F_{obs}^{-1}[F_{sim}(x_{sim})] \quad (5.2)$$

where x_{cor} is bias corrected value, $F_{sim}(x_{sim})$ is CDF of the simulated data, $F_{obs}(x)$ is CDF of the observed data, and F_{obs}^{-1} is inverse CDF (quantile function) of the observed data.

5.2.8. Rainfall–Runoff Modeling

Rainfall–runoff modeling can be conducted using various distributed and semi-distributed hydrological models. According to Ghonchepour et al. (2021), factors such as modeling objectives, hydrologic conditions, limitations, assumptions, and data availability should guide model selection. In this study, the HEC-HMS model was chosen for its suitability in simulating rainfall–runoff processes under varying LULC and climatic conditions, aligning well with the study’s objectives. HEC-HMS is a physically based, semi-distributed model widely recognized for its effectiveness in flood modeling (Acharya et al., 2013; Sanyal et al., 2014; Tibangayuka et al., 2022). It is compatible with the input data used in this study, including rainfall, streamflow, LULC, soil, and DEM data. Its semi-distributed structure facilitates accurate flow simulation at the subwatershed scale, which is critical for identifying

flood source areas. Furthermore, HEC-HMS has been thoroughly tested and shown to perform well in modeling floods in similar watersheds within the UBN basin of Ethiopia (Jemberie et al., 2016; Tassew et al., 2019).

The HEC-HMS model consists of several key components (managers), including basin models, meteorological models, time-series data, and control specifications (USACE, 2008). The basin model defines the physical characteristics of the watershed, such as subwatersheds, river reaches (networks), junctions, outlets, and others, along with relevant hydrological parameters. The meteorological model specifies the type of rainfall data used in the simulation. The time-series data component is used to input rainfall and streamflow data, which are essential for driving the model. Lastly, control specification manages or sets the simulation time step, duration, and output intervals. These components work together to simulate hydrologic processes and provide flood hydrographs.

In this study, rainfall–runoff simulations in the HEC-HMS model involved subwatershed delineation (basin model), entering rainfall and streamflow data, model selection (for runoff volume, direct runoff, and routing), parameter estimation and sensitivity analysis, model calibration and validation, and flood hydrograph simulations under changing LULC and climate conditions as detailed in the subsequent sections.

5.2.8.1. Subwatershed Delineation

Subwatershed delineation was performed using a 30 m resolution SRTM-DEM via the GIS tools in HEC-HMS 4.11, as this version is integrated with GIS components. The process involved setting up the coordinate system (projection), terrain reconditioning, filling sinks, drainage line processing, identifying streams, defining outlets, and delineating subwatersheds. Since the middle and upper portions of the Gumara watershed lie in steep gradient areas (slope greater than 15%), the 30 m DEM resolution could introduce inaccuracies, particularly in calculating flow direction and accumulation. These limitations may result in misrepresentation of the river network of the watershed. To address this issue, DEM reconditioning techniques, such as stream burning and sink filling, were applied to improve the representation of hydrological features. Additionally, during subwatershed delineation, the homogeneity of various watershed characteristics, such as soil, LULC, elevation, and stream networks, was considered for merging similar smaller subwatersheds into one.

5.2.8.2. Rainfall and Streamflow Data

This study utilized daily rainfall data from RF-MERGE (1981–2019), rainfall DDF curves for return periods of 5, 10, 25, 50, and 100 years, and rainfall for both historical and future periods to simulate streamflow. Observed streamflow data for the Gumara River (1981–2019) were also employed to

compare with simulated flows during model calibration and validation, focusing on selected flood events.

5.2.8.3. Model Selection

In the HEC-HMS, there are various models for computing runoff volume, direct runoff, and channel flow routing. For this study, the Soil Conservation Service Curve Number (SCS-CN) (Cronshey, 1986), SCS unit hydrograph (SCS-UH) (Cronshey, 1986), and Muskingum channel routing (Cunge, 1969) models were selected for modeling runoff volume, direct runoff, and channel flow routing, respectively.

I. Modeling runoff volumes (loss model)

Models available in the HEC-HMS generally compute runoff volume by subtracting the sum of various losses from the accumulated rainfall. Among these models, the Soil Conservation Service Curve Number (SCS-CN) method was selected for this study because it can compute runoff volume for a given rainfall event as a function of HSGs, LULC, and antecedent soil moisture conditions.

In the SCS-CN model, the excess rainfall (R_e) at a given time t is the rainfall in excess of the infiltration capacity and other losses and can be computed as:

$$R_e = \frac{(R - I_a)^2}{R - I_a + S} \quad (5.3)$$

where R is the accumulated rainfall depth at time t ; I_a is the initial abstraction (loss); and S is the maximum retention potential of the watershed. Considering the analysis findings from many experimental watersheds, the SCS-CN provides an empirical relationship of S and I_a , which is given as $I_a = 0.2S$. Then, the expression of R_e at a given time t becomes:

$$R_e = \frac{(R - 0.2S)^2}{R + 0.8S}, \text{ where } (R \geq 0.2S) \quad (5.4)$$

The maximum retention (S) can be computed as a function of the CN via the following equation.

$$S = \frac{25400 - 254 \text{ CN}}{\text{CN}} \quad (5.5)$$

In this study, 30 m spatial resolution gridded runoff CN maps were generated by considering soil and LULC characteristics (raster files), as well as the average antecedent moisture conditions (AMC-II). For the soil moisture condition, the AMC-II was accounted for because it represents a standard condition commonly used in hydrological modeling. The gridded CN maps were prepared via the ARC-GIS 10.4 environment (Redlands, 2011). The process involved preparing input data by aligning raster files (LULC and soil) to the same resolution, coordinate system, and extent; reclassifying LULC

and HSG maps; combining them; and assigning curve numbers using a lookup table with a raster calculator. Figure 5.5 shows the gridded runoff curve numbers for both the historical and future periods generated based on these procedures. The results indicate that the CN values under the BAU scenario are relatively greater than those under the governance (GOV) scenario. This is attributed to the expansion of cultivated land and settlement areas under the BAU scenario. As a result, the maximum retention potential of the watershed will reduce, which may lead to an increase in peak flow occurrence due to higher surface runoff volumes. The composite CN for each subwatershed was estimated on the basis of the mean value of raster grids (pixels) within the boundaries of the subwatershed area. Similarly, the composite CN for the entire watershed was calculated as the mean value of raster grids within the boundary of the whole watershed.

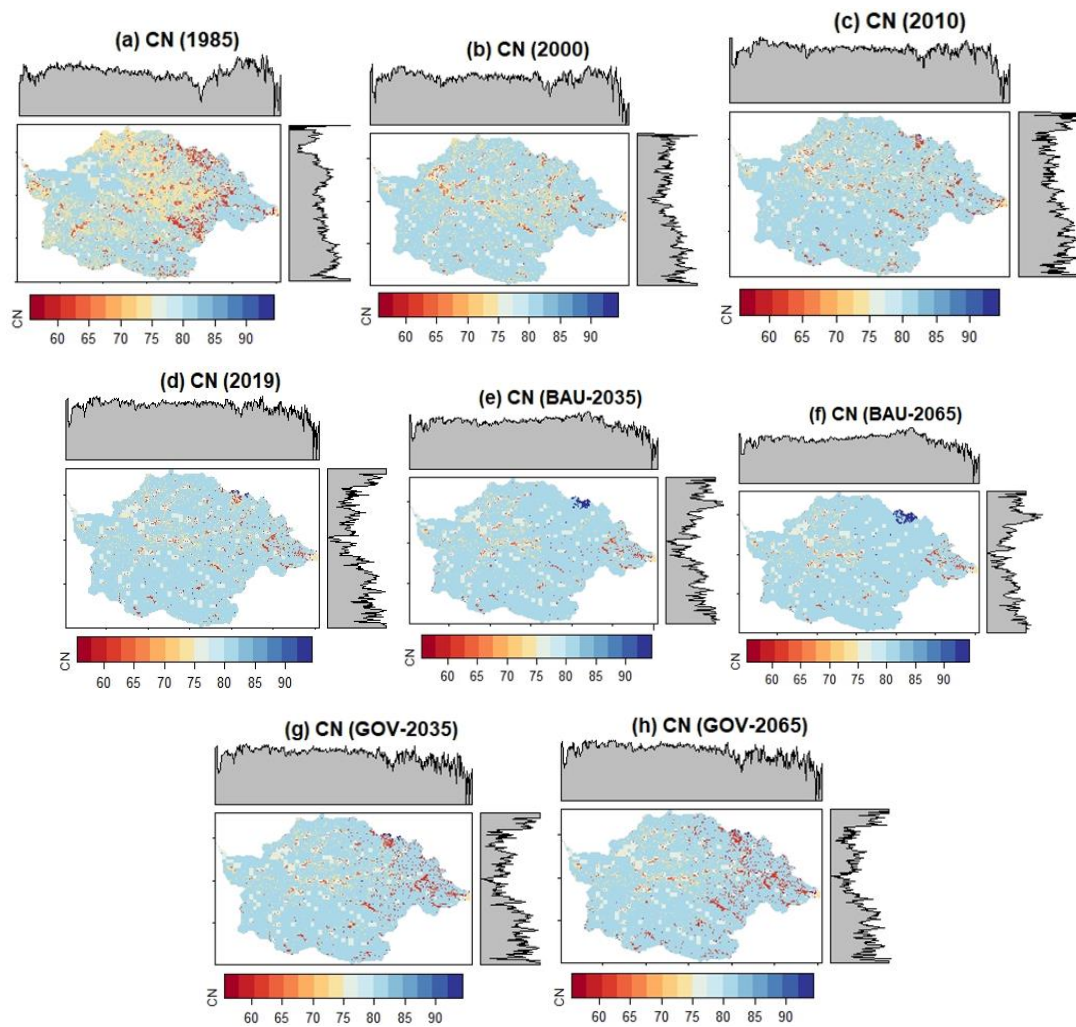


Figure 5.5. A 30 m spatial resolution gridded runoff curve numbers for the historical years (a–d) and future scenarios (e–h).

II. Direct runoff (transform model)

In the HEC-HMS model, several empirical and conceptual models are available to transform excess rainfall into direct runoff. Among these, the SCS unit hydrograph (SCS-UH) model (Cronshey, 1986) was selected for this study. The key parameter of this model is the lag time (T_{lag}), which represents the time difference between the center of mass of excess rainfall and the peak of the SCS-UH. Although the assumption of a single-peak hydrograph is a limitation of the SCS-UH, it was chosen because its parameters can be estimated from the physical characteristics of the watershed, specifically in relation to the time of concentration T_c . For this model, T_c can be computed via the Kirpich equation (Kirpich, 1940), and T_{lag} is then calculated as 0.6 times T_c :

$$T_c = 0.0195 \left(L^{0.77} / S^{0.385} \right) \quad (5.6)$$

where T_c is the time of concentration (min.), L is the length of the longest flow path (meter), and S is the average channel slope (m/m).

III. Channel flow (routing model)

From the available flow routing models in the HEC-HMS model, the Muskingum routing model was selected for this study. This model uses a finite difference approximation of the continuity equation and is widely used for flood routing (Chow et al., 1988). It accounts for flow attenuation resulting from the storage effect of the channel as flood flows travel through it.

The Muskingum routing model computes channel storage as follows:

$$S_t = K[XI_t + (1 - X)O_t] \quad (5.7)$$

where S_t , I_t , and O_t are storage, inflow, and outflow at time t , respectively; K is the travel time of the flood wave through the routing channel; and X is a dimensionless weight factor ($0 \leq X \leq 0.5$). For this study, the Muskingum routing model parameters (K and X) were determined through model calibration.

5.2.8.4. Model Sensitivity Analysis

Sensitivity analysis is a critical step in hydrological modeling aimed at reducing uncertainty and identifying model parameters that significantly influence the model's output (Song et al., 2015; Tibangayuka et al., 2022). In this study, sensitivity analysis was conducted for the parameters of the runoff volume (loss) and transform models by varying each parameter individually while keeping the others constant (local sensitivity analysis). Each parameter value was adjusted by $\pm 25\%$, and the relative percentage change in peak discharge was assessed for each simulation. The sensitivity of each

parameter was evaluated on the basis of the magnitude of the change in peak flow. The relative change in peak flow as a percentage was computed via the following equation:

$$\text{Relative change (\%)} = \frac{Q_{new} - Q_{base}}{Q_{base}} \times 100 \quad (5.8)$$

where Q_{new} is the peak flow after changing the parameter and where Q_{base} is the peak flow from the baseline simulation. In this study, model sensitivity analysis was performed for selected events that occurred from 13 to 31 August 2010.

5.2.8.5. Model Calibration and Validation

Model calibration and validation were performed to match the observed and simulated data for selected events. Both automated and manual calibrations were employed to obtain better agreement between the simulated and observed flow events through iterative adjustments of the model parameters. The performance of the model during calibration and validation was evaluated through graphical comparison (visual comparison) and statistical performance measures such as the coefficient of determination (R^2), Nash–Sutcliffe efficiency (NSE), root mean square error ($RMSE$), and percent bias ($PBIAS$). These performance measures were selected from different categories: R^2 from standard regression-based methods, NSE from dimensionless methods, and $RMSE$ and $PBIAS$ from error-based statistical methods (Legates & McCabe Jr, 1999).

R^2 expressed in Equation (5.9) describes the proportion of the variance in the observed data explained by the model-simulated data.

$$R^2 = \frac{\sum_{i=1}^N (O_i - \bar{O})(S_i - \bar{S})}{\sqrt{\sum_{i=1}^N (O_i - \bar{O})^2} \sqrt{\sum_{i=1}^N (S_i - \bar{S})^2}} \quad (5.9)$$

where O_i is the i th observed discharge value for the event being evaluated, S_i is the i th simulated discharge value for the event being evaluated, $\bar{O}$ is the mean of the observed discharge values, $\bar{S}$ is the mean of the simulated discharge values, and N is the total number of observations. R^2 values range from 0 to 1 (inclusive), with higher values indicating less error variance, and values higher than 0.5 are generally considered acceptable values (Van Liew et al., 2007).

The NSE is a dimensionless statistical performance measure that describes the relative magnitude of the residual variance (noise) compared with the observed data variance (information) (Nash & Sutcliffe, 1970). NSE is expressed as shown in Equation (5.10):

$$NSE = 1 - \frac{\sum_{i=1}^N (O_i - S_i)^2}{\sum_{i=1}^N (O_i - \bar{O})^2} \quad (5.10)$$

NSE ranges from $-\infty$ to 1 ($-\infty < NSE \leq 1$), where $NSE = 1$ indicates good agreement between the observed and simulated values, $0 < NSE \leq 1$ is generally considered acceptable, and $NSE \leq 0$ indicates poor or unacceptable model performance.

$RMSE$ expressed in Equation (5.11) describes the standard deviation of the model prediction error.

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (O_i - S_i)^2} \quad (5.11)$$

The optimal value of $RMSE$ is 0, which indicates perfect agreement between the observed and simulated values.

$PBIAS$ indicates the average tendency of the model-simulated values to be higher or lower than the observed values (Gupta et al., 1999). It is given as shown in Equation (5.12):

$$PBIAS (\%) = \frac{\sum_{i=1}^N (O_i - S_i)}{\sum_{i=1}^N O_i} \times 100 \quad (5.12)$$

The optimal value of $PBIAS$ is 0, with low values indicating accurate model simulation. Positive $PBIAS$ values indicate overestimation, whereas negative values indicate model underestimation. According to Moriasi et al. (2007), $-25\% < PBAS < 25$ is an acceptable range for discharge simulation.

In this study, model calibration was performed for two selected events: Event-1, which occurred from 1 July to 31 August 1996, and Event-2, which occurred from 5 July to 31 July 2008. Model validation was conducted via Event-3, which occurred from 2 August to 27 August 2014. These events were specifically chosen to account for periods with high flood peaks.

5.2.9. Flood Source Area Identification (FSAI)

Flood source area identification (FSAI) is an important approach for identifying the main sources of downstream flooding. It helps rank subwatersheds on the basis of their contribution to peak flood magnitude at the main watershed outlet. In this study, FSAI was performed using the UFR, which was introduced by Saghafeian and Khosroshahi (2005). In the UFR approach, the contribution of each subwatershed can be computed as:

$$FI_n = \frac{Q_{all} - Q_{all-n}}{Q_{all}} \times 100 \quad (5.13)$$

$$fi_n = \frac{Q_{all} - Q_{all-n}}{A_n} \quad (5.14)$$

where FI_n is the gross flood index of the n th subwatershed in percent, Q_{all} is the outlet peak discharge in m^3/s when all the subwatersheds are included in the base simulation, Q_{all-n} is the outlet peak

discharge in m³/s when n th subwatersheds are excluded from the simulation, fi_n is the flood index of the n th subwatershed (m³/s/km²) based on the area of the subwatershed, and A_n is the area of the n th subwatershed in km².

In the UFR approach, the subwatershed with the highest flood index value is ranked first (indicating the greatest contribution to peak discharge), whereas the subwatershed with the lowest flood index value is ranked last, indicating the least contribution. In this study, a calibrated HEC-HMS model incorporating all subwatershed components was first developed. The flood indices FI and fi for each subwatershed were subsequently calculated by disconnecting or eliminating a chosen subwatershed unit while maintaining the connections of the other subwatersheds. This process was repeated for all subwatersheds, allowing for a comprehensive analysis. In this regard, the analysis was also conducted under different conditions to investigate the impacts of LULC changes on the flood index values.

5.2.10. Combined Impacts of LULC and Climate Change on High-Flows

The combined impacts of LULC and climate change on high flows, specifically on the annual maximum (AM) 1-day flows, were analyzed by simulating historical and future conditions using the calibrated HEC-HMS model, driven by AM 1-day rainfall. To assess these impacts on high-flow extremes, flow duration curves (FDCs) were constructed from the AM flow series. The FDC construction process involved (1) sorting AM flows in descending order, (2) ranking the AM flows, (3) calculating the probability of exceedance for each flow value, and (4) plotting the AM flow series on the y-axis against the probability of exceedance on the x-axis. In this study, the probability of exceedance was calculated using the Weibull formula:

$$P = \frac{m}{N+1} \times 100 \quad (5.15)$$

where P is the probability of exceedance (%), m is the rank of the flow value, and N is the total number of flow data points.

5.3. Results

5.3.1. Mean Monthly and Annual Rainfall

Figure 5.6 presents the mean monthly rainfall of the study watershed, estimated using both observed data and GCM-simulated rainfall data. Observed rainfall estimates were derived by merging ground-based observations with three GRFPs (MSWEP, CHIRPS, and ERA5-Land) using the RF-MERGE approach, which enhances accuracy by integrating diverse sources. Historical and future GCM-simulated rainfall estimates were derived from statistically downscaled and bias-corrected ensemble

means from the CMIP5 (MIROC5, MRI-CGCM3, CanESM2, and MPI-ESM1-2-LR) and CMIP6 (MPI-ESM1-2-LR, MRI-ESM2-0, CNRM-CM6-1, and BCC-CSM2-MR) models.

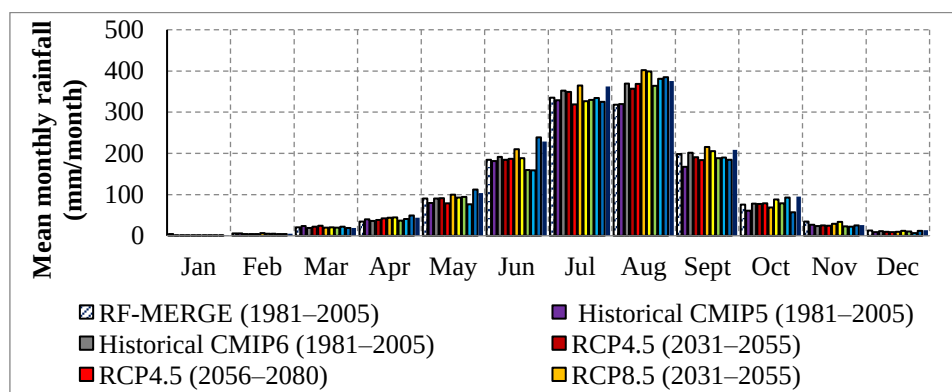


Figure 5.6. Historical and projected mean monthly rainfall (mm/month) of the Gumara watershed,

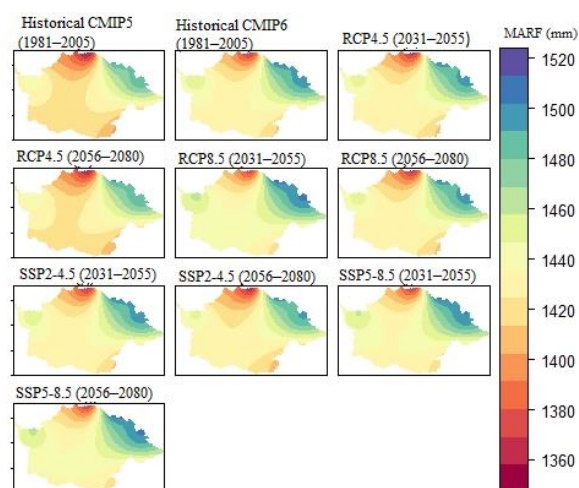


Figure 5.7. Spatial distribution of mean annual rainfall (MARF) in the historical (1981–2005) and two future periods, near-future (2031–2056) and far-future (2056–2080), under different climate scenarios.

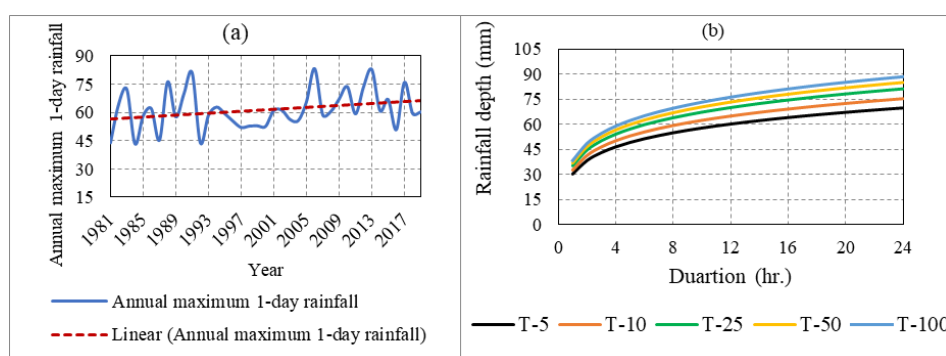


Figure 5. 8. (a) Temporal variation of the long-term annual maximum (AM) 1-day rainfall series from RF-MERGE estimates (1981–2019) and (b) depth–duration–frequency (DDF) curve developed from RF-MERGE rainfall. In panel (a), the red line illustrates the increasing linear trend of annual maximum 1-day rainfall.

Results indicate that the GCMs effectively captured observed rainfall patterns, despite projected increases in rainfall under RCP and SSP scenarios. Approximately 80% of the watershed's rainfall occurs during the main rainy season (June to September), consistent with the regional monsoon. For the historical period (1981–2005), the mean annual rainfall was estimated to be 1336 mm based on RF-MERGE data, while CMIP6 models estimated a slightly higher mean annual rainfall of 1379 mm. For future simulations, the highest projected mean annual rainfall was 1495 mm under the SSP5-8.5 scenario (2056–2080), indicating an expected increase in mean annual rainfall in the future period. These findings align with previous studies (Alaminie et al., 2021; Ayalew et al., 2022; Chakilu et al., 2023), which similarly reported projected increases in rainfall in the region.

Figure 5.7 illustrates the spatial distribution of mean annual rainfall (MARF) in the Gumara watershed for both the historical and future periods. The spatial distribution patterns are similar for both periods, with the primary difference being an increase in rainfall during the future period. Overall, the mean annual rainfall in the watershed ranges from approximately 1320 mm to 1560 mm, with the highest rainfall values concentrated in the northeastern part of the watershed and the lowest rainfall occurring in the northern part (Figure 5.7).

5.3.2. Design rainfall and depth–duration–frequency (DDF) curve

Design rainfall for the study watershed for various return periods was estimated by fitting the AM 1-day rainfall extracted from RF-MERGE estimates (Figure 5.8a) to candidate distributions. The goodness-of-fit test identified the GEV distribution as the best fit. Consistent with this finding, similar studies (Benyahya et al., 2014; Fischer et al., 2012) have reported the reliability of the GEV distribution for predicting extreme rainfall indices, such as the AM 1-day rainfall. The estimated design rainfall values for a 1-day duration using the GEV distribution were 70 mm, 75 mm, 81 mm, 85 mm, and 88 mm for the 5-, 10-, 25-, 50-, and 100-year return periods, respectively. However, to analyze flood occurrence, shorter-duration rainfall depths are often required for hydrological models. For this, a DDF curve for a 1-h duration was developed using a regional equation. Figure 5.8b presents this DDF curve, which predicts extreme rainfall intensity over various durations and return periods.

5.3.3. Annual maximum (AM) 1-day rainfall

The historical and projected annual maximum 1-day rainfall series were extracted from CMIP5 and CMIP6 multimodal ensemble means. The extracted 1-day rainfall was converted to hourly distributed rainfall using a regional equation and subsequently used to simulate the annual maximum flow series. The box plot in Figure 5.9 illustrates the distribution of the extracted data. The Figure summarizes the minimum, first quartile (Q1), median, third quartile (Q3), and maximum values of the rainfall data.

The blue dashed lines indicate the full range of data (minimum and maximum values) across the study periods. As shown, the data exhibit high variability across all periods, with an increase in future periods relative to historical values. Across all periods, the extracted maximum 1-day rainfall ranges from 23 mm to 83 mm, with the highest values observed under the SSP climate scenarios.

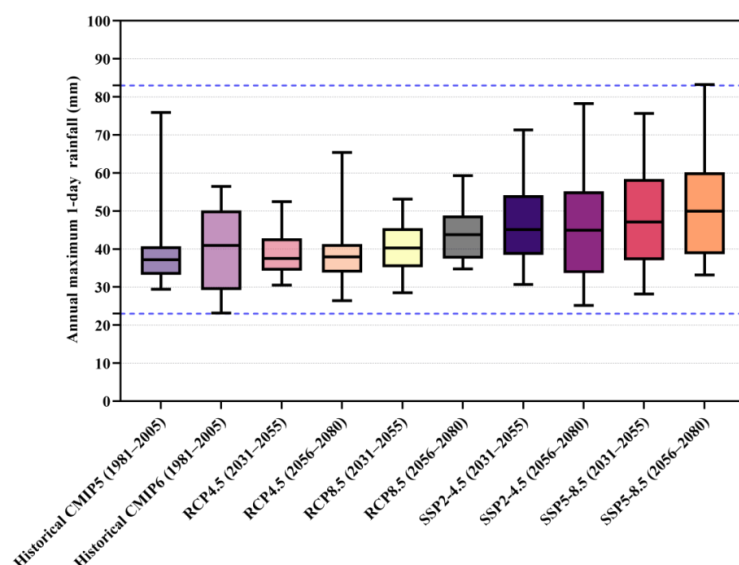


Figure 5.9. Box plot of historical (1981–2005) and projected (2031–2080) annual maximum (AM) 1-day rainfall.

5.3.4. LULC Change Analysis

LULC maps of the study watershed for the historical (1985, 2000, 2010, and 2019) and future (2035 and 2065) years were extracted from our previous work (Belay et al., 2024b), which analyzed the entire Gumara watershed. Figure 5.10a,b present the percentage coverage of different LULC classes for both the historical and future years, respectively. During the historical period, a significant increase in cultivated land and settlements was observed at the expense of a decrease in other land use classes. From 1985 to 2019, the percentage area of cultivated land and settlements increased from 63.70% (800.07 km²) to 88.39% (1110.18 km²) (Figure 5.10a). In contrast, the percentage areas of forest, shrubland, and grassland decreased from 4.98%, 28.21%, and 2.35% to 1.97%, 7.88%, and 0.59%, respectively (Figure 5.10a). These findings align with previous studies by Anteneh & Mohammed (2020) and Chakilu & Moges (2017), which also reported an increase in agricultural cultivation in the region.

Figure 5.10b shows the predicted percentage area of each LULC class in the study watershed for the years 2035 and 2065 under the BAU and GOV scenarios. Under the BAU scenario (which is based on the current trend of LULC change), cultivated land is expected to dominate, covering 91.34% and 91.78% of the area in 2035 and 2065, respectively, at the expense of decreases in other LULC classes

(forest, shrubland, and grassland). Conversely, under the GOV scenario (which is based on the green legacy initiative program), forest cover is predicted to increase, reaching 50.98 km² (4.06%) in 2035 and 66.06 km² (5.26%) in 2065. In this scenario, the expansion of cultivated land will be more controlled than in the BAU scenario. These findings are consistent with a study conducted in the upper Awash basin of Ethiopia by Gebresellase et al. (2023), which indicated an increase in agricultural lands and settlements under the BAU scenario and improvements in forests under the GOV scenario.

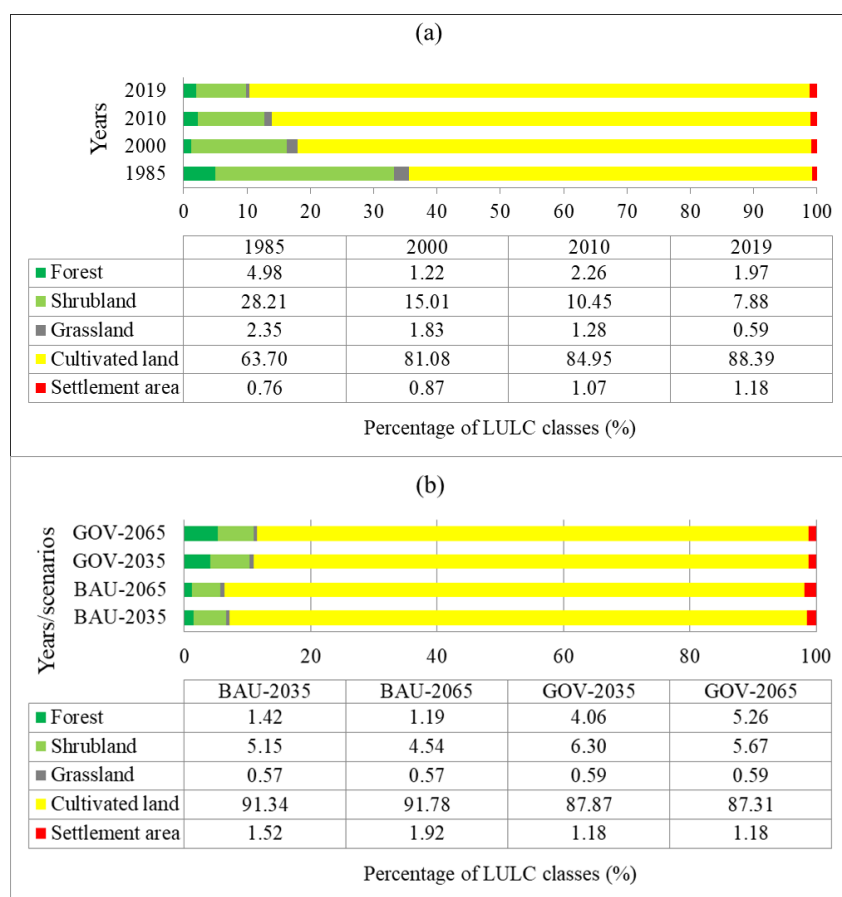


Figure 5.10. Percentage coverage of land use and land cover (LULC) classes of the Gumara watershed. (a) Historical years (1985, 2000, 2010, and 2019) and (b) future years (2035 and 2065) under the business-as-usual (BAU) and governance (GOV) scenarios.

5.3.5. Hydrological Modeling

5.3.5.1. Delineated Subwatersheds

Accounting for the homogeneity of various watershed characteristics, such as soil, LULC, elevation, and stream networks the Gumara watershed was delineated into eight subwatersheds, labeled W1 to W8 (Figure 5.11). The area of the subwatersheds ranges from 99.9 km² (W6) to 215 km² (W4) (Figure 5.11). Table 5.3 also presents the computed subwatershed (area and slope) and stream characteristics (length and slope).

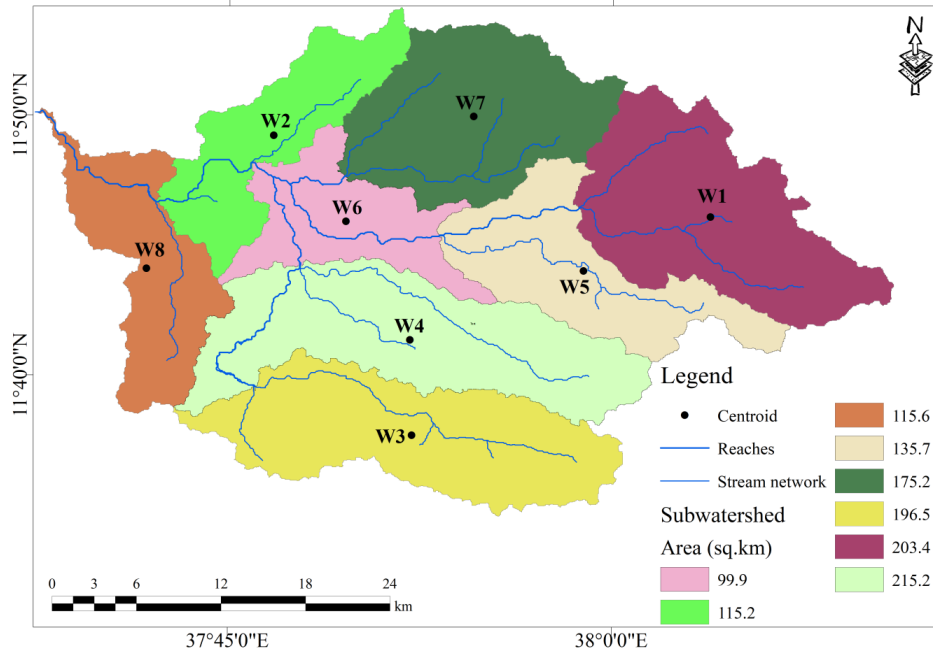


Figure 5.11. Delineated subwatershed's area, centroids, and stream network of the Gumara watershed as delineated in the HEC-HMS model.

Table 5.3. Characteristics of subwatersheds (area, slope, longest flow path length and slope, centroidal flow path length and slope, and drainage density).

Subwatershed	Area (km ²)	Subwatershed Slope (%)	Longest Flow Path Length (km)	Longest Flow Path Slope (%)	Centroidal Flow Path Length (km)	Centroidal Flow Path Slope (%)
W1	203.4	24.20	30.8	4.952	11.4	1.89
W2	115.2	13.10	28.9	1.748	13.3	0.35
W3	196.5	15.00	34.0	1.39	14.2	1.13
W4	215.2	19.40	34.2	2.287	13.0	1.06
W5	135.7	24.20	35.9	3.118	15.1	1.94
W6	99.9	14.50	25.8	1.871	10.3	0.18
W7	175.2	19.70	27.2	2.936	10.0	1.10
W8	115.6	15.40	33.6	1.999	21.0	0.97
Gumara	1256.7					

5.3.5.2. Model sensitivity analysis

Sensitivity analysis was performed to prioritize parameters for calibration and improve model efficiency. In this study, sensitivity analysis of the HEC-HMS model was conducted on key parameters, including CN , which controls runoff volume; I_a , which influences the proportion of rainfall lost before runoff begins; and T_{lag} , which affects the timing of peak discharge. For this analysis, flow events from August 13 to August 31, 2010 were considered (Figure 5.12). The results indicate that the CN was the most sensitive parameter. A direct relationship between flow and the CN was observed: increasing the CN resulted in higher discharge, while decreasing the CN led to lower discharge. Specifically, a 25%

increase in the CN led to a 9.79% rise in peak discharge, while a 25% decrease in the CN caused a 12.71% reduction in peak discharge (Table 5.5). These findings are consistent with studies by Tassew et al. (2019) in the Gilgel Abay catchment and Zelelew & Melesse (2018) in a small watershed in northwest Ethiopia, both of which also identified the CN as the most sensitive parameter. In contrast, I_a and T_{lag} were less sensitive, with minimal impact on peak discharge. Furthermore, since the SCS-CN method assumes uniform soil, land use, and rainfall conditions within a subwatershed, the model output (runoff volume) may be subject to uncertainties in watersheds with diverse topography, such as varying slopes and elevations. To address this limitation, it is crucial to adjust CN to local conditions based on field surveys and topographic data.

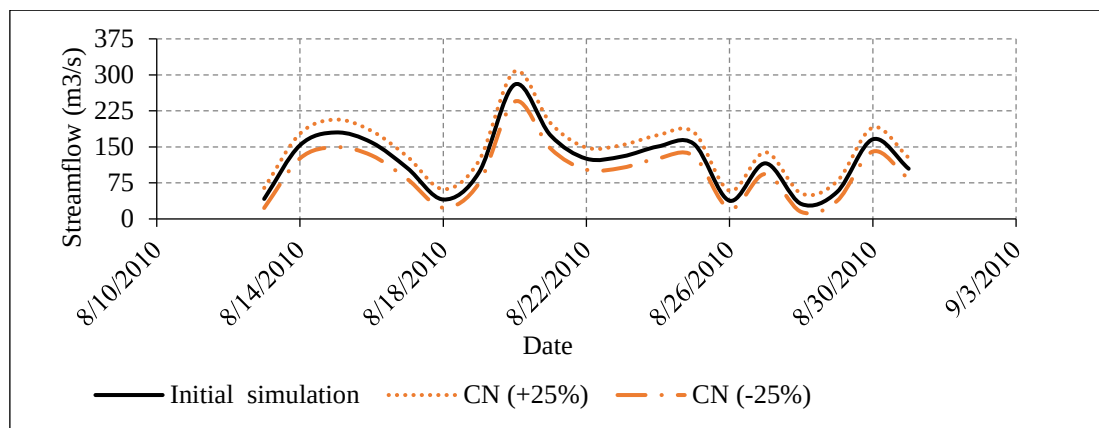


Figure 5.12. Model sensitivity analysis for the runoff curve number (CN) from 13 August to 31 August 2010

Table 5.4. Changes in peak discharge due to changes in the runoff curve number (CN) with $\pm 25\%$ for selected events (from 13 August to 31 August 2010).

Simulation	Peak Discharge (m^3/s)	Change in Peak Discharge (%)
Initial simulation	280	—
$CN (+25\%)$	307.4	9.79
$CN (-25\%)$	244.4	-12.71

5.3.5.3. Model Calibration and Validation

Model calibration and validation were performed for selected events. These events were chosen on the basis of the availability of gap-free discharge data and discharge series with high flood peaks. Figure 5.13 presents a comparison of the observed and simulated discharge hydrographs for these selected events.

In flood modeling, the most critical aspect of the hydrograph is the peak discharge, as it is the peak that has the potential to cause flooding downstream. In this study, the model adequately captured the

timing of the hydrograph peaks, although it tended to slightly overestimate peak discharge during calibration and underestimate during validation (Figure 5.13 and Table 5.5).

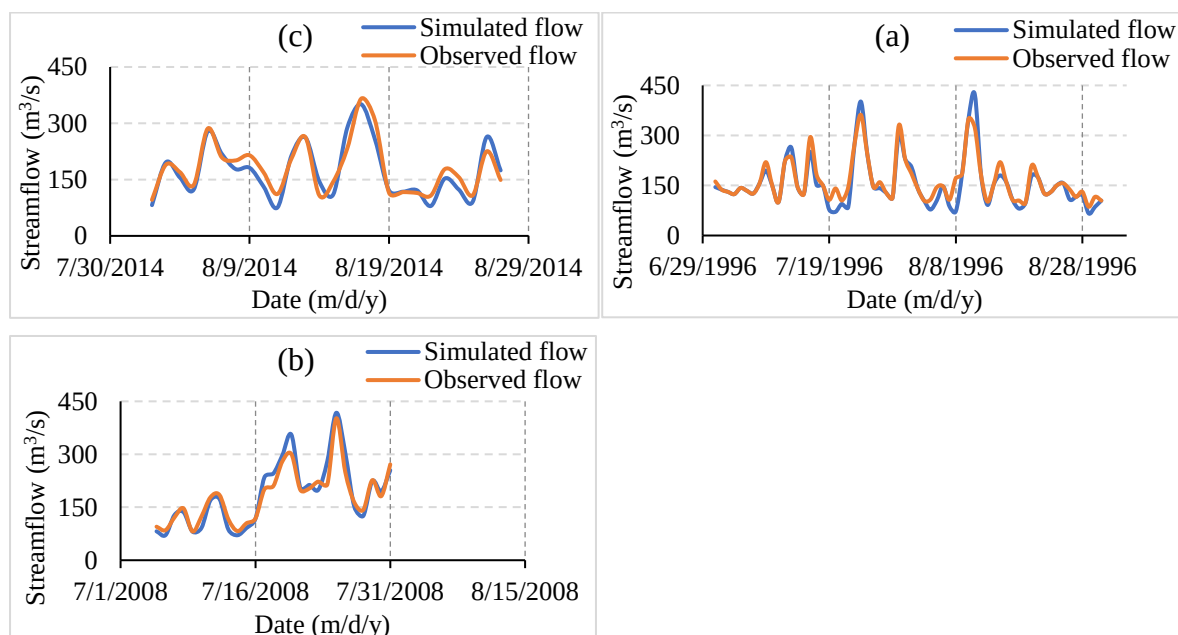


Figure 5.13. Observed and simulated discharge for selected events: (a) Event 1 (calibration), from 1 July to 31 August 1996; (b) Event 2 (calibration), from 5 July to 31 July 2008; (c) Event 3 (validation), from 2 August to 27 August 2014.

Table 5.5 summarizes the observed and simulated peak discharge and model performance evaluation results during the calibration and validation periods in terms of R^2 , NSE , $RMSE$, and $PBIAS$. The observed and simulated discharges were in close agreement. For example, an R^2 value of 0.89, NSE value of 0.82, $RMSE$ value of 27.1 m³/s, and $PBIAS$ value of -5.19% were found for Event 1 (calibration). Like during the calibration period, the observed and simulated discharges closely agreed during the validation period (Event 3), with R^2 value of 0.87, NSE value of 0.85, $RMSE$ value of 26.7 m³/s, and $PBIAS$ value of -3.99%. According to Moriasi et al. (2007), the statistical performance measures computed in this study are within an acceptable range, as the R^2 and NSE values exceed 0.5, and the $PBIAS$ values fall within $\pm 25\%$ for all events, indicating minimal error. Similarly, previous studies have demonstrated the effectiveness of the HEC-HMS model in simulating discharge in the UBN basin of Ethiopia. For instance, Tassew et al. (2019) applied HEC-HMS in the Gilgel Abay catchment, UBN basin of Ethiopia, and achieved R^2 values between 0.68 and 0.95 and NSE values ranging from 0.63 to 0.92 during calibration and validation for selected flow events, indicating acceptable model performance. Similarly, Yilma and Kebede (2023) used HEC-HMS in the Dabus subbasin, achieving calibration results with $R^2 = 0.81$ and $NSE = 0.78$, while validation yielded $R^2 = 0.87$ and $NSE = 0.79$, indicating the reliability of the HEC-HMS model for rainfall-runoff simulations.

These findings suggest that the HEC-HMS model can reliably simulate discharge in watersheds with topographic, soil, and LULC characteristics similar to the Gumara watershed. Table 5.6 also presents the calibrated (optimal) parameter values of the HEC-HMS model for the runoff volume (loss), direct runoff (transform), and routing components. These calibrated parameter values fall within the acceptable ranges specified in the HEC-HMS Technical Reference Manual (USACE, 2000).

Table 5.5. Model performance evaluation during calibration and validation.

Event	Peak Discharge (m ³ /s)		Performance Evaluation			
	Observed	Simulated	RMSE (m ³ /s)	R	NSE	PBIAS
Event 1 (calibration)	362	423.6	27.1	0.89	0.82	-5.19
Event 2 (calibration)	402	417.7	25.69	0.94	0.88	1.95
Event 3 (validation)	365.5	350.8	26.70	0.87	0.85	-3.99

Table 5.6. Calibrated model parameter values for the runoff volume, direct runoff, and routing models.

Runoff Volume Model: SCS-Curve Number			Direct Runoff Model: SCS-Unit Hydrograph		Routing Model: Muskingum Model		
Subwatershed	Initial Abstraction (mm)	Curve Number	Subwatershed	Lag Time (min.)	Reach	Muskingum K (hr.)	Muskingum X (hr.)
W1	15.2	77	W1	106	R1	1	0.45
W2	14.9	77	W2	150	R2	0.76	0.50
W3	14.3	78	W3	186	R3	0.15	0.35
W4	14.3	78	W4	155	R4	0.1	0.30
W5	14.9	77	W5	142	R5	0.58	0.50
W6	15.5	77	W6	134	R6	1.1	0.50
W7	15.2	77	W7	118	R7	1.17	0.45
W8	14.3	78	W8	160	R8	0.36	0.40

5.3.6. Return Period-Based Peak Discharge and Runoff Volume Simulation

Flood and runoff volume hydrographs were simulated in the calibrated HEC-HMS model. Figure 5.14a,b compare the peak discharge and total runoff volume of simulated hydrographs under different LULC conditions based on DDF curves of different return periods. From the results, increases in peak discharge and runoff volume were observed in the study watershed from 1985 to 2019. Among the simulation results, maximum peak discharge values of 211.7, 278.5, 359.5, 416.7, and 452.7 m³/s were found for the 5-, 10-, 25-, 50-, and 100-year return periods, respectively, under LULC-2019 (Figure 5.14a). For the same period, runoff volume values of 5.9, 7.6, 9.6, 11.05, and 11.7 mega cubic meters (MCM) were found for the respective return periods (Figure 5.14b)

Historical observations from 1981 to 2019 indicate that the average peak flood magnitude of the Gumara River was approximately 260.0 m³/s, closely matching the simulated peak flood magnitudes for the 5- and 10-year return periods. The simulated results also align with historical flood events recorded during the main rainy months (July and August) in 1996, 2006, 2008, 2014, and 2019, which caused significant inundation of cultivated lands and rural settlements downstream of the Gumara watershed (Alemu & Assaye, 2020; OCHA, 2019). Furthermore, previous studies (Nigusie et al., 2021; Tegegne et al., 2020) that employed at-site flood-frequency analysis within the Gumara watershed reported peak flood magnitudes comparable to the simulated results of this study.

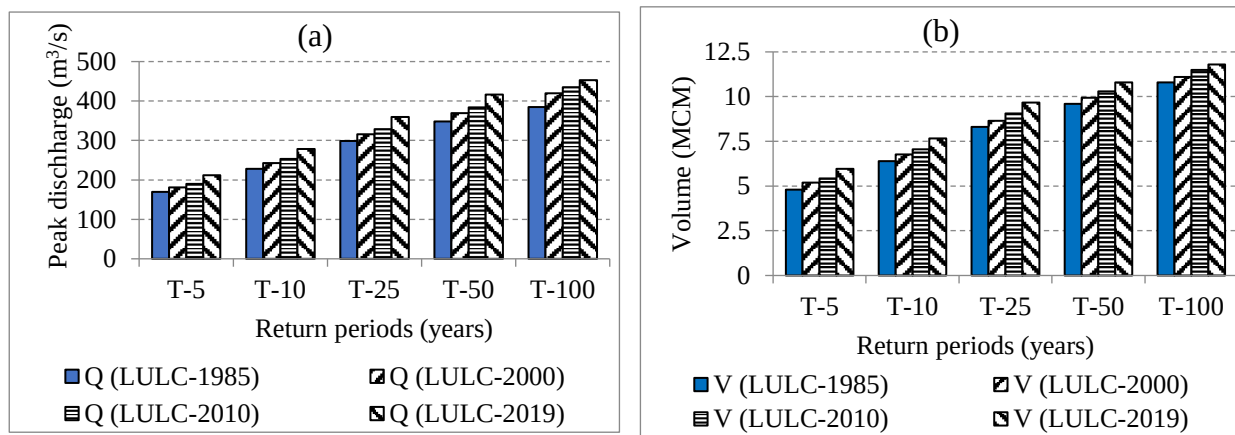


Figure 5.14. (a) Comparison of simulated peak discharge (Q) under various land use conditions across different return periods and (b) comparison of simulated runoff volume (V) under various land use conditions across different return periods.

Table 5.7 also shows the relative changes in peak discharge and runoff volume between two different LULC conditions (LULC-1985 to LULC-2019). The results indicate that the relative effect of LULC change decreases in flood peaks and runoff volumes of higher return periods, which is consistent with previous studies (Chen et al., 2009; Noori et al., 2016; Saghaian et al., 2008). For example, the LULC change from 1985 to 2019 increased the peak discharge by 38.7% for a 5-year return period but only by 22.4% for a 100-year return period. Similarly, the LULC change from 1985 to 2019 increased the runoff volume by 24.9% for a 5-year return period but only by 17.6% for a 100-year return period. This could be due to the diminishing impact of land use changes for higher return periods, such that further increases in rainfall do not significantly affect peak discharge (Abdulkareem et al., 2018). The analysis results also show that the impact of LULC change is more noticeable on peak discharge than on runoff volume.

Table 5.7. Changes in peak discharge and runoff volume for different return periods between LULC-1985 and LULC-2019.

Return Period	Peak Discharge (m ³ /s)			Runoff Volume (MCM)		
	1985	2019	Change (%)	1985	2019	Change (%)
T-5	169.4	211.7	24.9	4.8	5.96	24.2
T-10	228.4	278.5	21.9	6.4	7.66	19.7
T-25	298.9	359.5	20.2	8.3	9.66	16.4
T-50	348.4	416.7	19.6	9.6	10.8	12.5
T-100	384.8	452.7	17.6	10.8	11.8	9.3

Historical observations from 1981 to 2019 indicate that the average peak flood magnitude of the Gumara River was approximately 260 m³/s, which aligns closely with the simulated peaks for the 5- and 10-year return periods of LULC-2019. The simulated return period-based peak flood magnitudes are also consistent with historical flood events recorded during the main rainy months (July and August) in the years 1996, 2006, 2008, 2014, and 2019. These events resulted in substantial inundation of cultivated lands and rural settlements downstream of the Gumara watershed.

5.3.7. Flood Source Area Identification (FSAI)

The ranking of subwatersheds on the basis of their contribution to peak discharge at the main outlet of the Gumara watershed was determined via the UFR approach (Saghafian & Khosroshahi, 2005). In this analysis, peak discharge was simulated in the calibrated HEC-HMS model using the DDF curve of the 50-year return period. Table 5.8 presents the peak discharge contributions and rankings of subwatersheds under different LULC conditions. According to column 3 in Table 5.8, subwatershed W1 generated the highest peak discharge values under LULC-1985 and 2000 (74.9 and 81.8 m³/s, respectively). In contrast, subwatersheds W2 and W6 generated the smallest peak discharge values under the respective LULC conditions (37.5 and 39.9 m³/s, respectively). Under LULC-2010 and 2019, subwatershed W4 generated the largest peak discharge values (84.6 and 90.7 m³/s, respectively), whereas W6 (42.9 m³/s) and W2 (51.4 m³/s) generated the smallest peak discharge values for the respective LULC conditions.

Additionally, subwatershed units or (flood source areas) were ranked on the basis of flood index values such as *FI* and *fi* (Table 5.8). According to the results, different ranking index values were found under different conditions. For example, under LULC-1985, the W2 subwatershed, which is seventh in terms of area and eighth in terms of peak discharge generation, acquired seventh and sixth ranks in terms of the *FI* and *fi* indices, respectively (Table 5.8, columns 2, 3, 6, 8). While it maintains the same *FI* rank under LULC-2000, it jumps to seventh in terms of the *fi* index. Similarly, under LULC-2010, the W8 subwatershed, which is sixth in terms of area and peak discharge generation, acquired the seventh rank in the *FI* index and sixth rank in the *fi* index (Table 5.8, columns 2, 3, 6, 8). However, it jumps to eighth and seventh ranks in terms of the *FI* and *fi* indices, respectively, under LULC-2019.

Table 5.8. Comparison of 50-year peak discharge generation in the Gumara watershed under different land use conditions.

Subwatershed	Area (km ²)	Q_n (m ³ /s)	Q_{all-n} (m ³ /s)	FI_n (%)	Priority Based on FI_n	fi_n (m ³ /s/km ²)	Priority Based on fi
LULC-1985							
W1	203.4	74.9	270.7	16.8	2	0.269	3
W2	115.2	37.5	297.5	8.6	7	0.242	6
W3	196.5	65.6	281.5	13.5	4	0.223	8
W4	215.2	67	266.5	18.1	1	0.274	2
W5	135.7	40.1	292.4	10.1	5	0.243	5
W6	99.9	42	295.1	9.3	6	0.303	1
W7	175.2	55.7	281.4	13.5	3	0.251	4
W8	115.6	40.6	298.9	8.1	8	0.229	7
Gumara	1256.7	325.4					
LULC-2000							
W1	203.4	81.8	310.8	15.8	2	0.287	5
W2	115.2	40.5	338.1	8.4	7	0.269	7
W3	196.5	69.6	324.1	12.2	4	0.229	8
W4	215.2	80.6	298.5	19.1	1	0.328	1
W5	135.7	50.8	328.8	10.9	5	0.297	4
W6	99.9	39.9	338.6	8.3	8	0.305	3
W7	175.2	73.4	313.2	15.1	3	0.319	2
W8	115.6	50.2	337	8.7	6	0.278	6
Gumara	1256.7	369.1					
LULC-2010							
W1	203.4	82.6	324.8	15.3	2	0.289	7
W2	115.2	45.5	348.7	9.1	6	0.303	5
W3	196.5	70.3	339.1	11.6	4	0.226	8
W4	215.2	84.6	309.6	19.3	1	0.344	1
W5	135.7	54.8	340.3	11.3	5	0.319	4
W6	99.9	42.9	350.4	8.7	8	0.332	3
W7	175.2	75.4	325.5	15.1	3	0.333	2
W8	115.6	51.1	350	8.8	7	0.291	6
Gumara	1256.7	383.6					
LULC-2019							
W1	203.4	89.7	352.8	15.3	3	0.314	6
W2	115.2	51.4	378.1	9.3	6	0.335	5
W3	196.5	76.6	369.1	11.4	5	0.242	8
W4	215.2	90.7	337.5	19.0	1	0.368	1
W5	135.7	61.1	368.6	11.5	4	0.354	4
W6	99.9	48.3	380.1	8.8	7	0.366	3
W7	175.2	83.4	352.3	15.5	2	0.367	2
W8	115.6	53	381.7	8.4	8	0.303	7
Gumara	1256.7	416.7					

where Q_n is the peak discharge (m³/s) for the n th subwatershed, Q_{all-n} is the peak discharge (m³/s) when the n th subwatershed is excluded from the simulation, FI_n is the gross flood index of the n th subwatershed (%), and fi_n is the flood index of the n th subwatershed (m³/s/km²).

Furthermore, previous studies (Abdulkareem et al., 2018; Saghafian et al., 2008) recommend the fi index for ranking because it considers changes in peak discharge per unit area, unlike the FI index,

which considers only changes in peak discharge. Therefore, more attention needs to be given to subwatersheds with high *fi* index values during prioritization to reduce runoff generation in these subwatersheds. Figure 5.15 shows the *fi* index of each subwatershed of the Gumara watershed for the baseline period. According to the results, W6 was the most runoff-generating subwatershed under LULC-1985, with a *fi* index value of 0.303, whereas W4 was the most runoff-generating subwatershed under LULC conditions of 2000, 2010, and 2019, with *fi* index values of 0.328, 0.34, and 0.368, respectively. These show the combined effects of LULC and other related factors such as the location of subwatersheds within the entire watershed, river routing, elevation, slope, LULC, stream network, reach length and slope, rainfall distribution, and other physical features of the watershed under study in prioritizing subwatersheds (Maghsood et al., 2019; Saghaian et al., 2008; Singh et al., 2021). The combined effects of these factors can be well simulated via hydrologic models such as the HEC-HMS model used in this study.

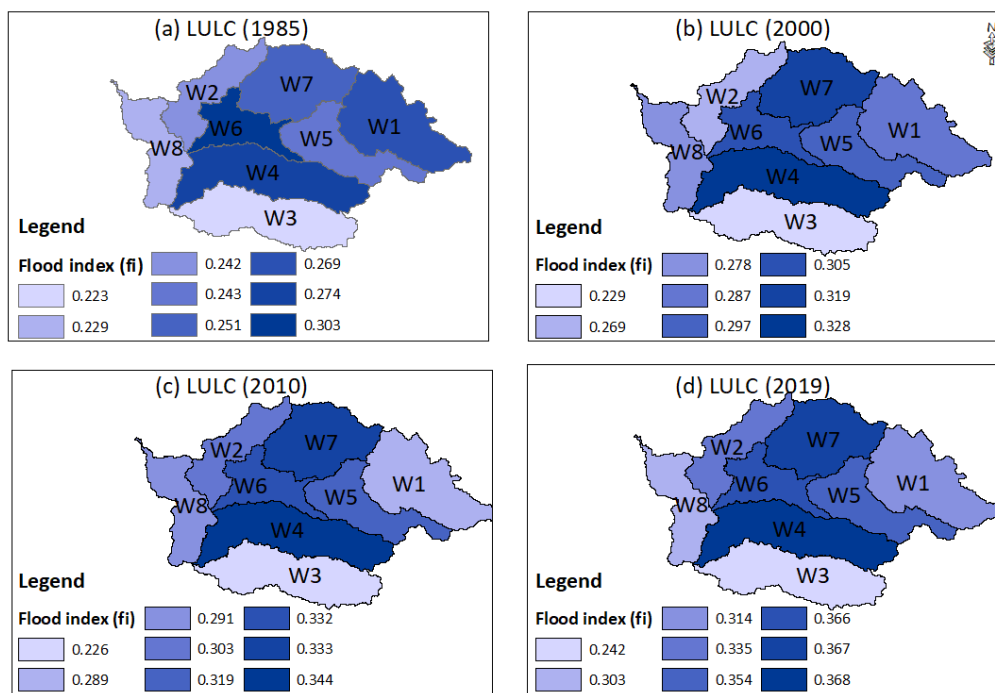


Figure 5.15. Computed flood index (*fi*) values estimated using the Unit Flood Response (UFR) approach for a 50-year return period peak discharge under different LULC conditions.

5.3.8. Combined impacts of LULC and climate change on high-flows

Historical and projected high flows of the study watershed were simulated using the calibrated HEC-HMS model, based on the AM 1-day rainfall. Table 5.9 below presents the mean AM flows, along with relative percentage change values. The results indicate that greater high-flow magnitudes were observed when future climate scenarios were combined with the BAU land use scenario compared to

the GOV scenario. Specifically, the highest flow value of 254.8 m³/s was found under the combined BAU-2065 land use and SSP5-8.5 (2056–2080) climate scenario, while the highest value of 230.6 m³/s was found under the combined GOV-2065 land use and SSP5-8.5 (2056–2080) climate scenario (Table 5.9).

Considering the relative change values, higher positive change values were observed when future climate scenarios combined with the BAU scenario ranged from 11.3% to 20.5% (Table 5.9). Among the computed changes under the BAU scenario, the greatest increase is projected under SSP5-8.5 (2056–2080) with a 20.5% increment. These significant increases in high flows in the future suggest a higher likelihood of more frequent flooding in the region.

In contrast, the change values are smaller when future climate scenarios are combined with the GOV land use scenario (Table 5.9), ranging from 5.9% to 9.0%. Among the computed changes under the GOV scenario, the greatest increase is projected under SSP5-8.5 (2056–2080) with a 9.0% increment. These lower change values can likely be attributed to afforestation efforts and controlled cultivation under the GOV scenario, which could enhance infiltration, reduce surface runoff, and contribute to more stable streamflow, especially during extreme rainfall events.

Table 5.9. Change in high flow of the Gumara watersheds under combined climate (RCP and SSP) and land use (BAU-2035, BAU-2065, GOV-2035, and GOV 2065) scenarios.

Scenario/Period	BAU Land use scenario	Flow under combined future climate and BAU land use scenario		GOV Land Use Scenario	Flow under combined future climate and GOV land use scenario	
		Mean Annual Maximum Flow (m ³ /s)	Change (%)		Mean Annual Maximum Flow (m ³ /s)	Change (%)
Historical CMIP5 (1981–2005)		188.1	–		188.1	–
Historical CMIP6 (1981–2005)		211.5	–		211.5	–
RCP4.5 (2031–2055)	2035	224	19.1	2035	200.5	6.6
RCP4.5 (2056–2080)	2065	209.4	11.3	2065	200.2	6.4
RCP8.5 (2031–2055)	2035	223.5	18.9	2035	204.0	8.5
RCP8.5 (2056–2080)	2065	225.7	20.0	2065	202.8	7.8
SSP2-4.5 (2031–2055)	2035	243.1	14.9	2035	225.1	6.4
SSP2-4.5 (2056–2080)	2065	237.4	12.3	2065	223.9	5.9
SSP5-8.5 (2031–2055)	2035	246.4	16.5	2035	226.4	7.0
SSP5-8.5 (2056–2080)	2065	254.8	20.5	2065	230.6	9.0

Furthermore, flow duration curves (FDCs) were constructed to assess the combined impact of LULC and climate change on high flows (Figure 5.16a,b). The results showed significant variations of high flows, particularly when different climate scenarios combined with the BAU land use scenario (Figure 5.16a) than combined with the GOV scenario (Figure 5.16b). The change in the high flow of the study watershed was also assessed by classifying high flow magnitudes into four categories depending on

different ranges of probability of exceedance (Q0–Q25, Q26–Q50, Q51–Q75, and Q76–Q100) (Table 5.10). Based on these categories, the change in high flow is more visible in the Q0–Q25. In this category (Q0–Q25), the SSP5-8.5 (2056–2080) scenario showed greater change in high flow when combined with the BAU-2065 and GOV-2065 land use scenarios as shown in Figure 5.16a and b, respectively.

In summary, the use of FDCs provides a robust approach to capture and compare the impacts of different LULC and climate scenarios on high-flow extremes. The increases in high-flow extremes under future scenarios, particularly in the BAU case, emphasize the urgent need for sustainable land use practices and climate adaptation strategies to mitigate future flood risks in the study watershed.

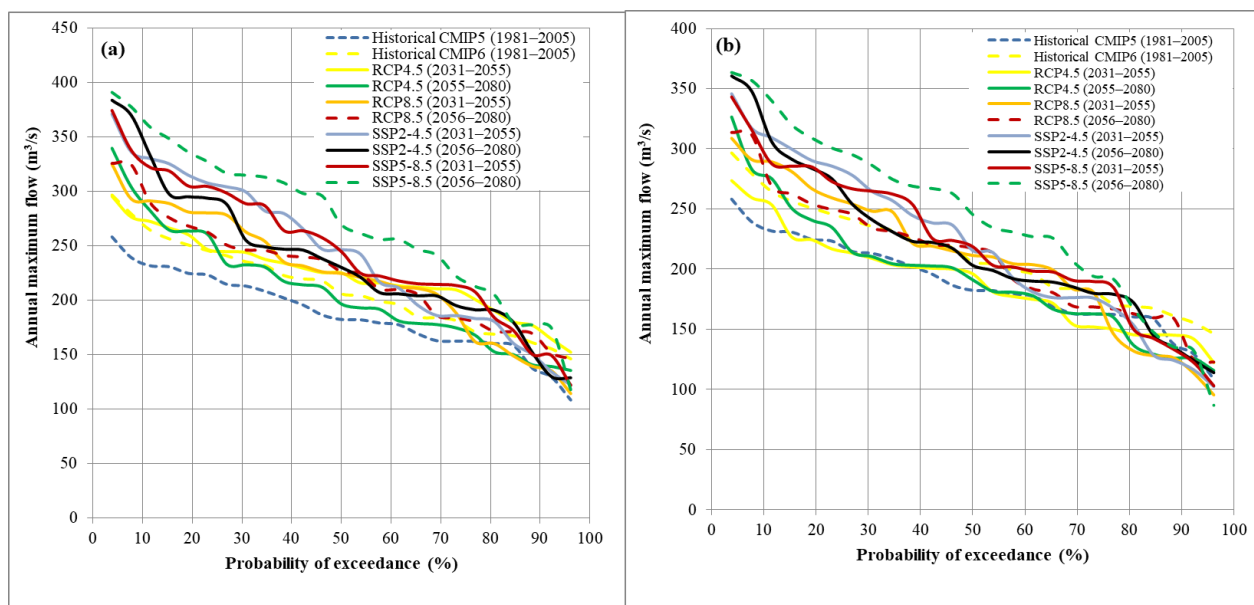


Figure 5.16. Comparison between historical and future annual maximum 1-day flow duration curves. (a) Future climate combined with the BAU land use scenario and (b) future climate combined with the GOV land use scenario.

Table 5.10. The mean annual maximum flow (Q) of the Gumara watershed, in m^3/s , across different probability of exceedance ranges, as estimated under combined climate and land use scenarios.

Scenario/Period	BAU Land Use Scenario	Flow under combined future climate and BAU land use scenario				GOV Land Use Scenario	Flow under combined future climate and GOV land use scenario			
		Q ₀ –Q ₂₅	Q ₂₆ –Q ₅₀	Q ₅₁ –Q ₇₅	Q ₇₆ –Q ₁₀₀		Q ₀ –Q ₂₅	Q ₂₆ –Q ₅₀	Q ₅₁ –Q ₇₅	Q ₇₆ –Q ₁₀₀
Historical CMIP5 (1981–2005)	–	234.7	200.4	172.3	142.8	–	234.7	200.4	172.3	142.8

Historical CMIP6 (1981–2005)	–	265.5	224.9	191.6	161.7	–	265.5	224.9	191.6	161.7
RCP4.5 (2031–2055)	2035	269.6	234.4	212.9	177.5	2035	242.4	203.5	168.4	141.7
RCP4.5 (2055–2080)	2065	285.7	219.5	182.9	147.8	2065	268.4	203.8	172.1	132.3
RCP8.5 (2031–2055)	2035	293.2	244.6	209.3	143.4	2035	282.7	231	197	123.6
RCP8.5 (2056–2080)	2065	291	241	203.3	165.1	2065	276.7	227.9	184.4	149.3
SSP2-4.5 (2031–2055)	2035	330.8	274.9	206.3	155.2	2035	308	247.8	186	132.1
SSP2-4.5 (2056–2080)	2065	328.7	250.5	206.3	162.1	2065	310.7	227.4	189.2	144.8
SSP5-8.5 (2031–2055)	2035	327	272	218.1	164.3	2035	298.3	245.1	196.9	139.3
SSP5-8.5 (2056–2080)	2065	356.4	302.2	247.2	177.8	2065	331.6	271.5	219.7	143.5

5.4. Discussion

5.4.1. FSAI and Analysis of High-Flow Extremes

The downstream part of the Gumara watershed is the most frequently flood-impacted area due to the high runoff contributed by the upstream watershed. This area, which includes cultivated land, rural and urban settlements, and infrastructure, is adversely affected by frequent floods, particularly during the main rainy months of July and August (Gashaw & Legesse, 2011; Nigusie et al., 2021). Land use and land cover (LULC) changes, such as deforestation and the expansion of cultivated land, combined with increases in extreme rainfall due to climate change in the upstream watershed, are key factors driving the increased frequency of floods in the region. For these reasons, this study focused on FSAI and the analysis of high-flow extremes under changing LULC and climate conditions in the upstream part of the watershed.

From the FSAI analysis, subwatersheds labeled from W1 to W8 showed varying flood index values under different LULC conditions. Consistent with these findings, a study by Saghaïan et al. (2008) in the Golestan watershed, located northeast of Iran, and Abdulkareem et al. (2018) in the Kelantan River basin, Malaysia, showed the significant contribution of LULC in identifying flood source areas. Overall, in the Gumara watershed, subwatersheds W4 and W6 were identified as the most significant flow contributors. This is because these subwatersheds were found as degraded areas where the expansion of agricultural lands has occurred (Figure 5.2) (Belay et al., 2024c). Additionally, the topographic features (such as steep slopes and elevation differences) and the stream network within these subwatersheds likely contribute to rapid runoff concentration, enhancing their flood-generating potential. This suggests that these two subwatersheds play the largest role in contributing to flooding in the downstream area, making them priority areas for intervention. To mitigate runoff and reduce downstream flooding, it is essential to implement measures in these subwatersheds that enhance infiltration. These measures could include effective land use management strategies (such as afforestation, reforestation, terracing, and contour farming), soil and water conservation practices (e.g., check dams and gabions), and green infrastructure solutions.

The projected high-flow extremes for the future period in this study consistently showed increases relative to the historical period. Notably, the percentage increases were higher when future climate scenarios were combined with the BAU land use scenario. This can be attributed to the fact that, under the BAU scenario, the clearing of forests and other vegetative cover for agricultural expansion leads to decreased infiltration rates and increased surface runoff, resulting in higher flows during extreme rainfall events. These findings are in line with previous studies (A. G. Mengistu et al., 2023; Teklay et al., 2021), which also projected an increase in streamflow under future climate scenarios combined with the BAU land use scenario. In contrast, when different climate scenarios were combined with the GOV land use scenario, the percentage increases were lower. This is because land use management strategies under the GOV scenario, such as afforestation, reforestation programs, and controlled expansion of cultivated land and settlements, are expected to enhance infiltration and reduce runoff during extreme rainfall events.

Among all simulations of high flows for future periods, the most alarming increase in high flows was observed under the SSP5-8.5 (2056–2080) climate scenario combined with the BAU-2065 land use scenario, consistent with recent studies (Kassaye et al., 2024; Mahato et al., 2022; Yalcin, 2024). These results indicate that the Gumara watershed will face more frequent floods during this period, which could significantly disrupt the socioeconomic conditions of the community, as their livelihoods depend on crop cultivation. To reduce the adverse impact of future flood events, this suggests a pressing need to implement various flood protection and adaptation strategies in the downstream part of the watershed. First, it is recommended that local governments implement strict land use management policies that promote afforestation and reforestation to counterbalance the impacts of climate change on flooding. Second, local communities, basin initiatives, and non-governmental organizations should actively participate in soil and water conservation activities. Third, the construction of flood protection infrastructure in the downstream areas, particularly near cultivated land and settlements, is essential to mitigate the adverse effects of flooding on socioeconomic activities and infrastructure. The feasibility of these flood protection and adaptation measures requires collaboration among local governments, non-governmental organizations, basin initiatives, and the local community.

Overall, this study investigated the impacts of LULC and climate changes on FSAI and high-flow extremes in the Gumara watershed. The identification of flood source areas provides valuable insights for prioritizing subwatersheds that contribute most significantly to peak discharges. This spatially explicit information can guide targeted interventions to mitigate flood risks. By integrating historical and future LULC scenarios with projected climate data, the findings indicate a substantial increase in high-flow extremes in future periods. These increases suggest the likelihood of more frequent flood

events, which could adversely impact downstream areas. In this regard, the study provides critical insights into future flood risks and offers a foundation for developing effective flood risk management strategies to mitigate the adverse impacts of frequent flooding in downstream areas. Furthermore, the methodology developed in this study, particularly the application of merged rainfall data from multiple data sources in flood studies, offers a significant contribution to improving hydrological simulations.

5.4.2. Generalizability of the Study Findings

The Gumara watershed, located in the UBN basin, has unique geographic and socio-economic characteristics. Geographically, it is characterized by steep upstream slopes and flat downstream floodplains. Socioeconomically, the watershed is dominated by rural areas with scattered settlements, where the livelihood is primarily based on a mixed farming system (crop cultivation and livestock raising). While these characteristics make it a valuable case study for assessing the impacts of LULC and climate change, they may limit the generalizability of findings. The results of this study may be most applicable to watersheds with similar socio-economic conditions and geographic settings. Regions with different geographic and socio-economic characteristics, such as urbanized areas or those with advanced flood management infrastructures, may experience varying hydrological responses. However, the study's methodological framework offers a transferable approach that can be adapted to other regions with comparable challenges.

5.4.3. Limitations of the Study and Future Research Directions

As mentioned in the methods section, historical and future climate scenarios (RCP and SSP) from GCMs are often associated with uncertainties (Enayati et al., 2021; Kaur & Kaur, 2023). To reduce these uncertainties, it is recommended to correct biases in climate models and use ensembles of multiple models instead of relying on a single model. In this study, bias correction of climate models and the ensemble mean of GCMs were employed to mitigate these uncertainties. Future research could explore various machine learning ensemble prediction (MLEP) approaches to further reduce uncertainties in climate models and use these outputs as inputs to hydrological models.

Both the BAU and GOV LULC scenarios considered in this study rely on assumptions about future socioeconomic and policy developments. However, these assumptions may not fully capture the uncertainties of future land use changes. For instance, the BAU scenario assumes continuity in current land use trends, while the GOV scenario assumes improvement of forest cover. However, sudden policy shifts and regional economic changes could significantly alter the trajectory assumed in these scenarios. In this context, future research could explore the uncertainties associated with these

scenarios by considering more intermediate scenarios to further reduce the uncertainties associated with land use projections.

In this study, the antecedent soil moisture was assumed to be at an average condition, as it represents a standard condition for hydrological modeling. Future research could integrate rainfall data with satellite-based soil moisture data to further enhance flood simulations using hydrological models.

Additionally, future research could extend this study by incorporating hydraulic flood modeling for downstream areas of the Gumara watershed. Using the outputs of this study as inputs for detailed hydraulic modeling would enable a more comprehensive analysis of flood inundation and hazard mapping in the region. This approach could provide valuable insights for flood risk management and inform targeted mitigation strategies.

5.5. Conclusions

This study assessed the impacts of LULC and climate changes on high-flow extremes in the Gumara watershed using the HEC-HMS model. Merged rainfall data (1981–2019) and multi-model ensemble means from CMIP5 and CMIP6 models were utilized for historical (1981–2005), near-future (2031–2055), and far-future (2056–2080) periods, with future climate scenarios projected under RCP4.5, RCP8.5, SSP2-4.5, and SSP5-8.5 pathways. Historical LULC maps (1985, 2000, 2010, and 2019) and projected LULC scenarios (BAU-2035, BAU-2065, GOV-2035, and GOV-2065) were incorporated to analyze the effects of LULC change on flood risk.

The long-term observation period (1981–2019) showed a significant increase in peak discharge under recent LULC conditions, with peak values rising by 24.9% for the 5-year return period and by 17.6% for the 100-year return period, indicating a decreasing influence of LULC changes with higher return periods. The flood source areas identified using the UFR approach revealed subwatersheds W4 and W6 as consistent contributors to high runoff across various LULC conditions, making them priority areas for flood mitigation efforts.

Future projections indicate a further increase in high flows, especially under the SSP5-8.5 (2056–2080) climate scenario combined with BAU-2065 land use, where flows are projected to increase by up to 20.5%, suggesting an increased flood risk in the region. In contrast, the GOV scenario, which promotes afforestation, shows a smaller flow increase of up to 9.0%, demonstrating that sustainable land management practices can help mitigate climate change impacts on extreme flows.

In summary, this study integrated the RF-MERGE, GIS, and HEC-HMS models to investigate the effects of LULC and climate changes on high-flow extremes in the Gumara watershed. The findings provide valuable insights for watershed managers and land use planners to prioritize subwatersheds

and develop effective flood risk management practices. The study suggests the coordinated participation of local governments, non-governmental organizations, basin initiatives, and communities to collaboratively mitigate the adverse effects of future flood events. Future research could expand on this work by using climate model ensembles based on MLEP approaches, integrating satellite-based soil moisture data, and conducting hydraulic flood modeling downstream of the Gumara watershed. These efforts would further inform flood mitigation strategies across the region.

CHAPTER 6

6. Flood Inundation Mapping Using the Google Earth Engine and HEC-RAS under Land Use/Land Cover and Climate Changes in the Gumara Watershed, Upper Blue Nile Basin, Ethiopia

This chapter has been published as:

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Abstract

Floods are among the most frequent and devastating climate-related hazards, causing significant environmental and socioeconomic impacts. This study integrates synthetic aperture radar (SAR)-based flood mapping via the Google Earth Engine (GEE) with hydraulic modeling in HEC-RAS to analyze flood dynamics downstream of the Gumara watershed, Upper Blue Nile (UBN) Basin, Ethiopia. A change detection approach using Sentinel-1 imagery was employed to generate flood inundation maps from 2017–2021. Among these events, flood events on July 22, August 3, and August 27, 2019, were used to calibrate the HEC-RAS model, achieving an F-score of 0.57, an overall accuracy (OA) of 86.92%, and a kappa coefficient (K) of 0.62 across the three events. Further validation using ground control points (GCPs) resulted in an OA of 86.33% and a K of 0.72. Using the calibrated HEC-RAS model, hydraulic simulations were performed to map flood inundation for return periods of 5, 10, 25, 50, and 100 years. Additionally, flood mapping was conducted for the historical period (1981–2005), near-future (2031–2055), and far-future (2056–2080) periods under extreme climate scenarios. The results indicate 16.48% and 27.23% increases in the flood inundation area in the near-future and far-future periods, respectively, under the SSP5-8.5 scenario compared with the historical period. These increases are attributed primarily to deforestation, agricultural expansion, and intensified extreme rainfall events in the upstream watershed. The comparison between SAR-based flood maps and HEC-RAS simulations highlights the advantages of integrating remote sensing and hydraulic modeling for enhanced flood risk assessment. This study provides critical insights for flood mitigation and sustainable watershed management, emphasizing the importance of incorporating current and future flood risk analyses in policy and planning efforts.

Keywords: Flood inundation mapping, Google Earth Engine, HEC-RAS, Land use/land cover, Climate change, Gumara watershed

6.1. Introduction

Traditional flood mapping relies primarily on ground-based observations and optical remote sensing images (Psomiadis et al., 2020). However, ground-based observations of flood extent, depth, and timing can be labor intensive and time consuming (Elkhrachy et al., 2021). Images from optical remote sensing are further hindered by extreme weather conditions, such as cloud cover, heavy rainfall, fog, and strong winds (Ouled Sghaier et al., 2018; Tiwari et al., 2020). To address these challenges, synthetic aperture radar (SAR)-based flood inundation mapping has emerged as a powerful alternative to traditional flood mapping approaches (Kumar et al., 2022; Tay et al., 2020; Tiwari et al., 2020). SAR sensors can penetrate adverse weather conditions and operate both day and night, making them invaluable for real-time and near-real-time flood mapping (Anusha & Bharathi, 2020; Pulvirenti et al., 2011). Additionally, the ability of SAR to capture high-resolution images makes it suitable for

accurately mapping flood extents, even in complex terrains (Grimaldi et al., 2020; Twele et al., 2016). Among the various SAR sensors available, the Sentinel 1A and 1B satellite missions launched by the European Space Agency (ESA) in 2014 and 2015 are frequently utilized for flood detection (Aldiansyah et al., 2024; Kumar et al., 2022; Nghia et al., 2022; G. Singh & Rawat, 2024).

Although SAR images are more efficient at flood mapping than optical remote sensing images are, the processes of downloading, storing, preprocessing, and mapping require a large volume of data storage and high computational resources (Passah et al., 2023). To overcome this, recent studies have widely used the Google Earth Engine (GEE), a cloud-based platform (Gorelick et al., 2017), for processing and analyzing a number of geospatial data, including SAR and Landsat imagery. Owing to its broad applicability, GEE has been increasingly used in recent studies for SAR-based flood mapping (Nghia et al., 2022; Pandey et al., 2022; Tiwari et al., 2020).

In SAR-based flood mapping, flooded pixels can be detected via various algorithms, including fuzzy logic (Amitrano et al., 2024; Perera & Lahat, 2015), active contour (Nobre et al., 2016), change detection (Clement et al., 2018a; Giustarini et al., 2012), and histogram-based thresholding approaches (Long et al., 2014a; Otsu, 1975). Among these algorithms, change detection is the most widely used, as it can be implemented in the GEE environment by comparing preflood and postflood images. For example, a study by Kumar et al. (2022) employed the change detection approach via GEE for flood extent mapping, which affects rice cultivation in Bihar State, India. Similarly, previous studies (Pandey et al., 2022; G. Singh & Rawat, 2024) demonstrated the application of the change detection approach for small- and large-scale flood inundation mapping studies.

For comprehensive flood risk assessment, it is necessary to map flood depth, water surface elevation, and velocity in addition to flood extent and timing under different land use/land cover (LULC) and climate scenarios (Anuthaman et al., 2023; Mzava et al., 2021). For this purpose, the Hydrologic Engineering Center-River Analysis System (HEC-RAS) model, developed by the US Army Corps of Engineers, is the most widely used tool for 1D, 2D, and combined 1D/2D hydraulic flood modeling (USACE, 2016). The latest version of HEC-RAS (6.5) is capable of performing 2D unsteady flow simulations on the basis of the full Saint-Venant and diffusion wave equations (Brunner, 2014). Following the release of this version with 2D modeling capabilities, several studies have been conducted in various basins and watersheds (Elkhrachy et al., 2021; Ezzine et al., 2020; Quiroga et al., 2016; Rangari et al., 2019). For example, Ongdas et al. (2020) highlighted the good performance of the HEC-RAS 2D model for flood hazard mapping under different scenarios. Costabile et al. (2020) demonstrated the applicability of the HEC-RAS 2D model in simulating floods in the Scuropasso Basin, Italy. Similarly, a study by Anuthaman et al. (2023) in the Adyar subbasin, India, showed its

ability to forecast flood inundation maps under changing LULC and climate conditions via outputs from a rainfall-runoff model. Furthermore, recent studies (Elkhrachy et al., 2021; Psomiadis et al., 2020) have highlighted the advantages of integrating the HEC-RAS model with remote sensing techniques, such as SAR-based flood mapping, to improve flood modeling accuracy and facilitate model calibration, particularly in the absence of observed flood data (e.g., flood depth and extent).

The downstream area of the Gumara watershed (study area) is one of the most frequently flood-affected areas in the upper blue Nile (UBN) basin of Ethiopia (Melkamu et al., 2022). Floods in this area cause the destruction of infrastructure, the inundation of agricultural lands, and the disruption of socioeconomic activities (Alemu & Assaye, 2020; W. Gashaw & Legesse, 2011). Factors such as extreme rainfall, land use and land cover (LULC) changes, and topographic and drainage characteristics contribute to the increased risk of flooding in this area. In this area, studies have been conducted using the HEC-RAS model (Nigusie et al., 2021) and Sentinel-1 SAR images based on a histogram-based thresholding approach (Melkamu et al., 2022). However, flood inundation mapping under changing LULC and climate conditions and rapid flood mapping via Sentinel-1 SAR images via the change detection approach have not been well investigated in the studied watershed.

Therefore, this study aims to utilize the GEE cloud-based platform and the HEC-RAS 2D hydraulic model to map flood inundation in the downstream region of the Gumara watershed. The SAR-based flood mapping accounted for flood events from 2017–2021, with the July and August 2019 flood events serving as calibrations for the HEC-RAS model. The HEC-RAS model was further validated and subsequently used to simulate flood inundation maps for various return periods (5, 10, 25, 50, and 100 years). Additionally, this study aims to generate flood inundation maps under extreme conditions for historical (1981–2005), near-future (2031–2055), and far-future (2056–2080) periods to assess changes in flood extents driven by land use and climate change. By addressing these objectives, this study provides valuable insights for flood risk mitigation and sustainable watershed management in the Gumara watershed.

6.2. Materials and Methods

6.2.1 Study Area

The flood-prone area that is part of the Gumara watershed is located within the UBN basin of Ethiopia (Figure 6.1). Geographically, it lies between 11° 48' N -11°57' N latitude and 37° 28' E - 37° 40' E longitude (Figure 6.1c). The flood-prone area considered in this study covers approximately 177.8 km². Topographically, the flood-prone area is relatively flat, with elevations ranging from 1779–1985 m above mean sea level (amsl). The watershed experiences a unimodal rainfall pattern, with a long rainy

season spanning June–September and a mean annual rainfall of 1,445 mm (Figure 6.2a). The streamflow of the Gumara River peaks during these months, especially in July and August (Figure 6.2b). Cultivated land is the dominant LULC class in both flood source and flood-prone areas (Belay et al., 2024b; Chakilu & Moges, 2017). Owing to its flat terrain and gentle slope, the flood-prone area is highly susceptible to frequent flooding caused by the overflow of the Gumara River. This vulnerability is intensified by extreme rainfall events and LULC changes in upstream areas (Dawit et al., 2019; Gashaw & Legesse, 2011).

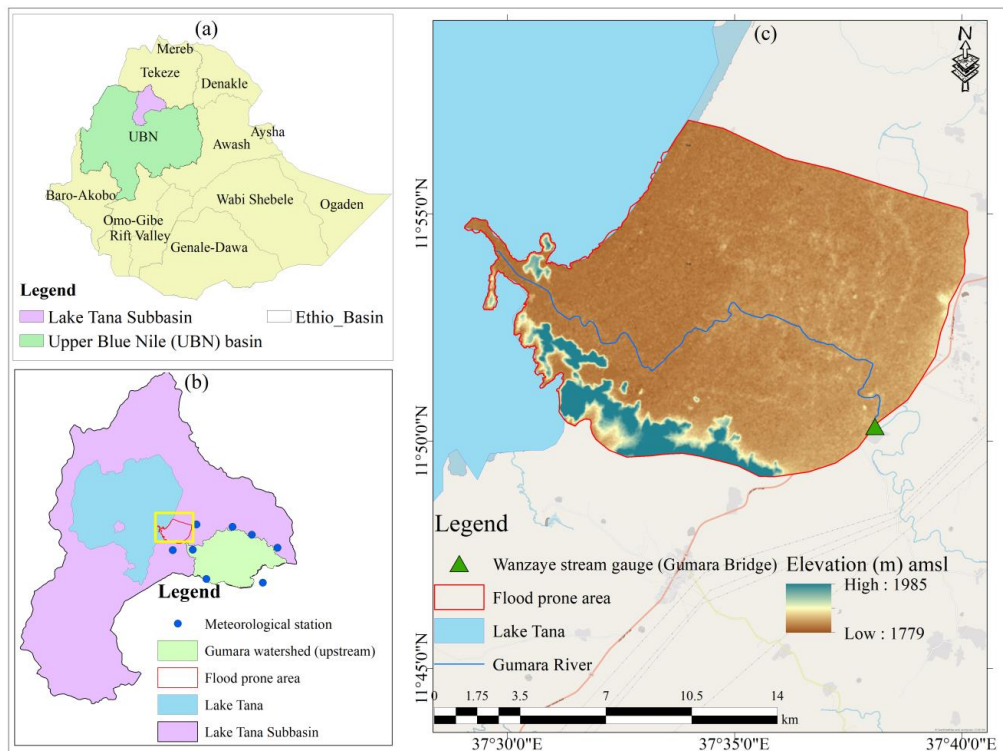


Figure 6.1. Location map of the study area. (a) The Upper Blue Nile (UBN) basin and the Lake Tana subbasin within the context of Ethiopia's 12 river basins, (b) the Gumara watershed in the context of the Lake Tana subbasin, and (c) detailed features of the study area, including the streamflow gauging station, flood-prone area, Gumara River (downstream section), and elevation map.

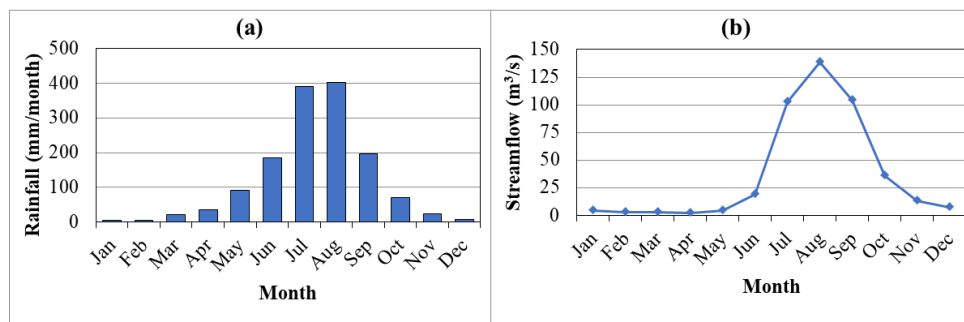


Figure 6. 2. (a) Mean monthly rainfall of the Gumara watershed (1981–2019) and (b) mean monthly streamflow of the Gumara River at the Wanzaye gauging station (1981–2019).

6.2.2 Data Used

The data for SAR-based flood mapping and hydraulic flood modeling were sourced from various providers. For SAR-based flood mapping, pre- and postflood Sentinel-1A Level-1 SAR ground range detection (GRD) scenes were accessed through the European Space Agency (ESA) Copernicus Programme (<https://scihub.copernicus.eu>) via the Google Earth Engine (GEE) data catalog. Time series flood inundation maps were generated via SAR data from 2017–2021, with January composite images representing preflood conditions and July–August composites representing postflood conditions each year. These images were captured in VH polarization (vertical transmit, horizontal receive), interferometric wide swath (IW) mode, and descending orbit pass mode, with a 10-meter spatial resolution and a 12-day temporal interval. The 2019 flood event was selected for comparison with hydraulic flood modeling. For this year, preflood images were obtained on January 11 and 23, whereas postflood images were acquired on July 22, August 3, and August 27, 2019.

To refine the flood extent maps, additional datasets were utilized. A 12.5-meter resolution digital elevation model (DEM) was obtained from the Alaska Satellite Facility (ASF) (<https://vertex.dac.asf.alaska.edu>) and used to generate the slope map. The derived slope map was then applied to enhance the accuracy of the flood extent map generated from the SAR data. The JRC Global Surface Water Map layer (Pekel et al., 2016), which depicts spatiotemporal changes in global water bodies, was also used to mask permanent and semipermanent water bodies from flood inundation maps.

For hydraulic flood modeling, the DEM obtained from the ASF was used as a primary input. Sample river cross-sections of the Gumara River (downstream), along with elevation data for high and low ground, were collected through field surveys and Google Earth images for terrain modification. The LULC map for 2019 was sourced from Belay et al. (2024b).

The observed daily time series discharge data (1981–2019) for the Gumara River at the Wanzaye gauging station were collected from the Ministry of Water and Energy (MoWE) of Ethiopia. These data served as the upstream boundary conditions for simulating the observed flood event. Additionally, daily observed rainfall data (1981–2019) were obtained from the Ethiopian Meteorological Institute (EMI). Inflow hydrographs of the upstream Gumara watershed for various return periods (5, 10, 25, 50, and 100 years), as well as for extreme conditions during the historical (1981–2005), near-future (2031–2055), and far-future (2056–2080) periods, were sourced from Belay et al. (2025) and used as

boundary conditions. In Belay et al. (2025), these inflow hydrographs for the upstream watershed were generated by counting future extreme rainfall and projected LULC data for the years 2035 and 2065.

Ground control points (GCPs) for flooded and nonflooded areas were collected to validate the hydraulic flood model. These GCPs were generated via Sentinel-2 imagery and field investigations in the most flood-affected areas. A Sentinel-2 Level-2A surface reflectance (SR) image from August 30, 2019, with a 10-meter spatial resolution, was accessed via GEE from the ESA for this purpose. This image was selected because it has minimal cloud cover, allowing for more accurate GCP generation in combination with information from field investigations.

6.2.3 Methodological Framework of the Study

In this study, SAR-based flood inundation maps were generated via Sentinel-1 SAR images within the Google Earth Engine (GEE) environment, while hydraulic flood modeling was conducted via HEC-RAS 2D. Figure 6.3 illustrates the overall methodological framework of the study. Details of the methods used are provided in the subsequent sections.

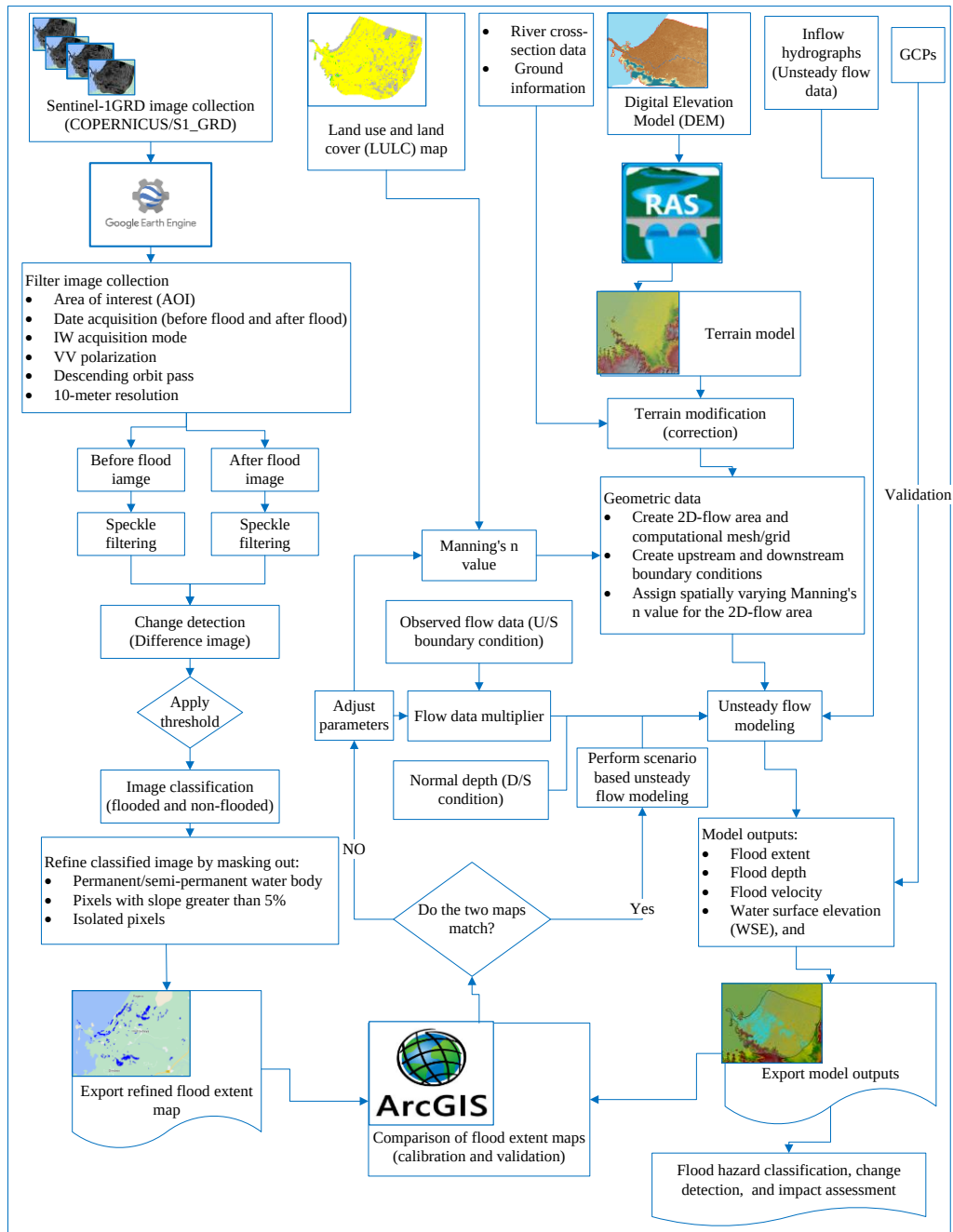


Figure 6.3. Overall methodological framework of the study.

6.2.4 SAR-Based Flood Inundation Mapping

SAR-based flood inundation mapping was conducted within the GEE environment. The process involved several steps: data acquisition and filtering of image collections, preprocessing, change detection, and refining and exporting flood extent maps.

6.2.4.1 Importing and Filtering of SAR Image Collection

Sentinel-1 SAR images before the flood (preflood) and during the flood (postflood) were acquired in GRD format via the GEE data catalog. To select a subset of SAR images, the image collection was filtered on the basis of various metadata properties, such as the filter bounds, date of acquisition, instrument mode, transmitter and receiver polarizations, orbit pass properties, and resolution. The shapefile of the flood-prone area was imported into the GEE environment as an asset and used as a filter bound. A composite of SAR images acquired for January 11 and 23, 2019, was used as the preflood image since this period was the dry season in the study area. Images acquired on July 22, August 03, and August 27, 2019 (during the flood) were used to map the floods that occurred on those dates. The images were acquired in IW instrument mode with VH polarization, a descending orbit pass, and a spatial resolution of 10×10 meters. The IW mode was selected because it is the primary acquisition mode for land surfaces.

A similar procedure was followed for importing and filtering SAR images from 2017–2021. Time series inundation maps were prepared via composites of January images as preflood conditions and composites of July–August images as postflood conditions instead of focusing on specific flood events. This approach aimed to map flood frequency in the region over a five-year period.

6.2.4.2 Preprocessing

Sentinel-1 SAR images often suffer from various types of errors and noise, such as geometric and radiometric distortions, thermal noise, and speckle (Filipponi, 2019; Lee et al., 1994). Therefore, these noises need to be corrected through preprocessing steps before the data can be used for flood inundation mapping. The GEE platform has already applied the following preprocessing steps: (i) Orbit file correction is used to update the metadata of the orbit. (ii) Border noise removal eliminates invalid data (e.g., low-intensity noise) at the edges of the scene. (iii) Thermal noise removal eliminates additive noise, such as discontinuities between subswaths in SAR scenes with multishwath acquisitions. (iv) Radiometric calibration is used to convert digital pixel values to calibrated SAR backscatter coefficients (σ°) on the basis of sensor calibration parameters. (v) Terrain correction is used to remove geometric distortion in SAR images. (vi) Convert σ° to decibels (dB) and use a logarithmic transformation of $(10 \cdot \log_{10} \sigma^\circ)$ to convert the unitless σ° to dB.

Sentinel-1 Level-1 GRD images, which have already undergone automated preprocessing steps, were used for this study. Despite these preprocessing steps, the images still contained speckle noise, which appeared as granular noise caused by the coherent nature of SAR imaging. To reduce the effects of speckle noise, speckle filtering or smoothing was applied to both preflood and postflood images.

Specifically, a refined Lee speckle filter (Lee et al., 1994) with a window size of 3x3 was employed within the GEE environment.

6.2.4.3 Change Detection and Thresholding

A change detection approach was employed to map the flood extent. This method involves dividing the postflood image by the preflood image to generate a difference image, which is then classified into a binary image representing flooded and nonflooded areas. To create the binary raster, a threshold value was applied to the difference image. The selection of an appropriate threshold value depends on various factors, including the type of flood, the characteristics of the SAR images, and the conditions of the surrounding area. The optimal threshold was determined through visual inspection and frequency distribution analysis (histogram thresholding) (Clement et al., 2018b; Long et al., 2014b). Since the frequency distributions of flooded and nonflooded pixels follow a bimodal pattern with two distinct peaks, the threshold was set at the transition zone (valley) between the two peaks.

Furthermore, the percentage area of flooded pixels was also computed to analyze the sensitivity of the flood extent to different threshold values, which could guide the determination of the optimal threshold value. Following these methods, the optimal threshold was determined for separating flooded pixels from nonflooded pixels.

6.2.4.4 Refining and Exporting Flood Extent Maps

To increase the accuracy of the flood extent map generated through the change detection approach, additional datasets were used to refine the results by eliminating overestimated flood areas. Among these, the JRC global surface water mapping layer dataset was used to exclude areas covered by permanent and semipermanent water, applying a seasonality threshold greater than 10 months per year. This dataset effectively masked water in wetlands and along lakes.

A slope layer derived from a 12-meter DEM was also used to exclude false positives in the flood mapping process. This is because steep areas are generally less prone to flooding, and any SAR-detected flooding in such regions is likely to be a false positive. For this study, flooded pixels in areas with slopes greater than 5% were masked out, following recommendations from previous studies (Loukili et al., 2025; SPIDER, 2019), to improve the accuracy of flood detection.

In SAR-based flood mapping, wet soil and certain vegetation (e.g., rice fields) may exhibit low backscatter similar to floodwater, potentially leading to misclassification (false positives) (Notti et al., 2018; Tupas et al., 2023). To address this issue, the connectivity of flooded pixels was assessed, and isolated flood pixels were removed to minimize noise and enhance the accuracy of the final flood map. Specifically, pixel connectivity was first analyzed via the GEE function recommended by UN-SPIDER

(SPIDER, 2019). Then, the pixels connected to eight or fewer neighbors were removed, as they were more likely to be false positives.

To compute the areal extent of the flood mapping output, the refined raster binary layer (flooded and nonflooded) prepared in GEE was exported, and final processing was performed in ArcGIS 10.4. The areal extent of the flooded area in m² was computed by summing the area of each flooded pixel. Additionally, to estimate the impact of flooding on cultivated land, spatial analyst and spatial statistics tools were used in the ARC-GIS environment for overlay analysis.

6.2.5 Hydraulic Flood Modeling

Hydraulic flood modeling was conducted via the HEC-RAS model (version-6.5). This model has the ability to perform 2D unsteady flow modeling on the basis of full shallow water (SW) and diffusion wave (DW) equations (Brunner, 2024a). These equations can perform detailed 2D channel and floodplain mapping with high flexibility (Akiyanova et al., 2023; Brunner, 2024b). From these equations, 2D-DW equations were chosen for this study, as these equations can perform unsteady flow modeling faster with high stability (Costabile et al., 2020).

The 2D-DW equation solver in HEC-RAS uses an implicit finite volume algorithm, as this algorithm provides improved stability and allows for performing flow simulations for larger computational time steps than finite difference and finite element methods perform (Chaudhry, 2008). The 2D-DWE are derived from mass conservation and momentum equations as described below:

Mass conservation equation: In 2D flood modeling, the mass conservation equation (also known as the continuity equation) governs how water depth changes over time and how water is transported within the floodplain (Brunner, 2024b; Robinson et al., 2019). This ensures that water is conserved in the model by considering both changes in water depth and the velocity field across the domain. The equation is expressed as:

$$\frac{\partial h}{\partial t} + \frac{\partial(hu)}{\partial x} + \frac{\partial(hv)}{\partial y} = 0 \quad (6.1)$$

where h represents the depth of the water, u represents the velocity of the water along the x -axis, v represents the velocity of the water along the y -axis, t represents time, and x and y represent location information. In equation (1), the first term represents ($\frac{\partial h}{\partial t}$) the rate of change in water depth over time), whereas the second ($\frac{\partial(hu)}{\partial x}$) and third ($\frac{\partial(hv)}{\partial y}$) terms represent the fluxes of water (the rates of flow of water) in the x and y directions, respectively.

Momentum equations: In 2D flood modeling, the momentum equation describes the movement of water on the basis of the forces acting on it (Brunner, 2024b; Robinson et al., 2019). In the 2D DW equation, the momentum equations are simplified by neglecting the inertia (acceleration) terms of the full dynamic equation, assuming that the flow is governed primarily by gravity and friction (Brunner, 2024b). The equation is expressed as follows:

A long x -axis:

$$S_{0x} - S_{fx} - \frac{\partial h}{\partial x} = 0 \quad (6.2)$$

Along the y -axis:

$$S_{0y} - S_{fy} - \frac{\partial h}{\partial y} = 0 \quad (6.3)$$

Where S_{0x} and S_{0y} are bed slopes in the x and y directions, respectively. $\frac{\partial h}{\partial x}$ and $\frac{\partial h}{\partial y}$ represent the slopes of the water surface in the x and y directions, respectively. S_{fx} and S_{fy} are the friction slopes in the x and y directions, respectively. The bed slope term expressed in the momentum equations can be computed from the underlying elevation data (DEM), whereas the friction slope terms are determined via Manning's equation, which relates friction (flow resistance) to depth and velocity.

$$S_{fx} = \frac{n^2 u \sqrt{u^2 + v^2}}{h^{4/3}} \quad (6.4)$$

$$S_{fy} = \frac{n^2 v \sqrt{u^2 + v^2}}{h^{4/3}} \quad (6.5)$$

where n is Manning's roughness coefficient; u and v are the velocity components in the x and y directions, respectively; h is the water depth; and $u^2 + v^2$ represents the total velocity magnitude.

The 2D flow model in HEC-RAS was set up using a 2D flow area to represent the floodplain. For this purpose, the RAS mapper of the HEC-RAS model was used to import terrain data and other features, create and refine geometric data, and visualize the HEC-RAS simulation results. Overall, hydraulic flood modeling involves terrain preprocessing, creating a 2D flow area and computational mesh, defining boundary conditions, assigning Manning's roughness value, and conducting unsteady flow analysis followed by output mapping. Details of these procedures are provided in the following Section.

6.2.5.1 Terrain Preprocessing

In the HEC-RAS model, terrain data are essential for determining the geometric and hydraulic properties of 2D computational meshes. In this study, a 12.5-meter resolution DEM was used to

develop the terrain model. The vertical accuracy of this DEM, expressed in terms of the root mean square error (RMSE), was found to be approximately 3.5 m. However, this DEM does not include the actual terrain beneath the water surface in the river, diversion channels, or other low-lying areas. To address these gaps, a total of 17 river cross-sections, the hydraulic properties of the diversion channel, and elevation data for low- and high-elevation areas were incorporated. These data were obtained from Google Earth by extracting elevation profiles (as supplementary data) and from field surveys. The collected information was then used to modify and improve the original terrain model. Figure 6.4 below shows the original and modified terrain models in Triangulated Irregular Network (TIN) format. The station and elevation data for the cross-sections, along with a comparison of elevation data from the DEM and ground observations, are provided in Appendix, C1-C3.

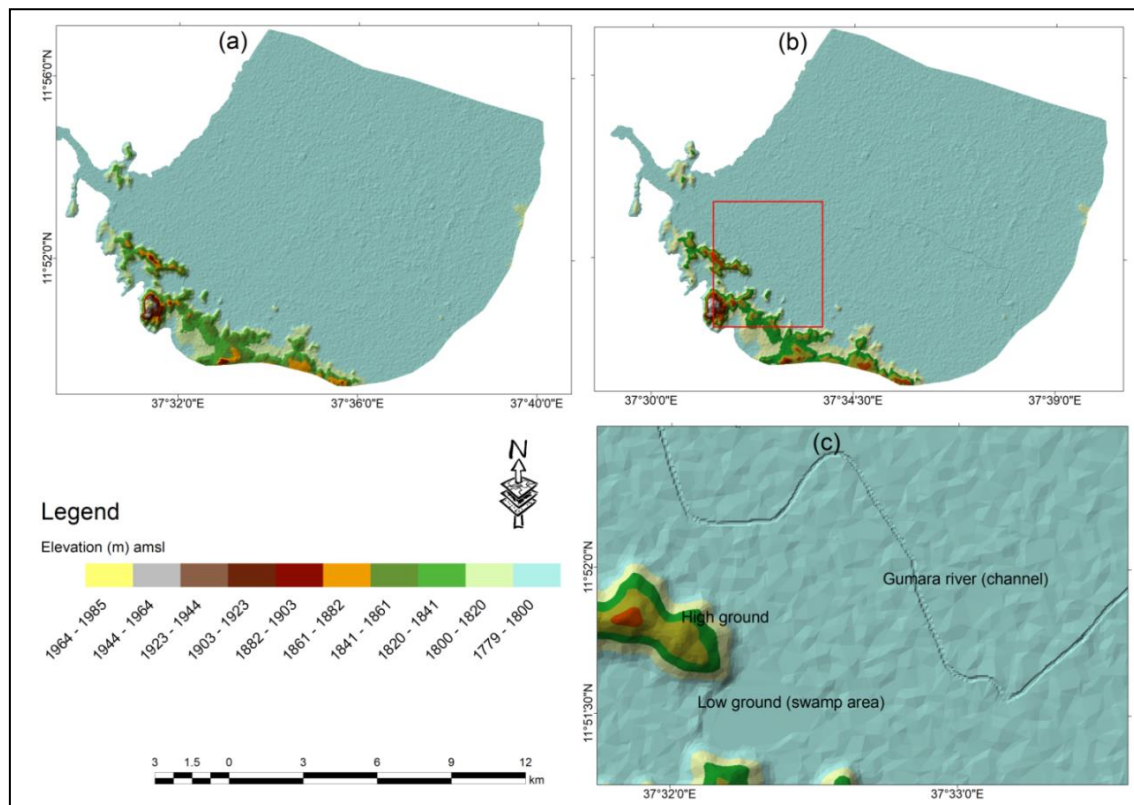


Figure 6.4. Terrain modification in triangular irregular (TIN) format. (a) Original terrain model, (b) modified terrain model, and (c) details of the modified terrain model showing the Gumara River (channel) and elevation variation in the floodplain area found at the left bank of the river.

6.2.5.2 2D Flow Area and Computational Mesh

In HEC-RAS, flood-prone areas can be delineated via background web-based satellite imagery, terrain models, and various map layers to accurately define floodplains (Brunner, 2024a). For this study, a 2D flow area was created for the downstream section of the Gumara River, extending from the Gumara Bridge at Wanzaye to the shores of Lake Tana. This area includes floodplains frequently affected by

riverine flooding, following previous studies (Mekuria et al., 2018; Nigusie et al., 2021) conducted in the downstream Gumara River watershed. During the delineation of the 2D flood area, high-elevation areas that could obstruct floodwater flow were primarily used as boundaries.

Following the creation of the 2D flow area, the next step was to generate the 2D computational grid/mesh. The computational grids consist of various shapes, including triangles, rectangles, squares, and polygons with up to eight sides. Each grid cell within the computational mesh includes a cell center, cell faces, and cell face points. The cell center is the computational point where the water surface elevation and depth are calculated. The cell faces are typically straight or multipoint lines that define the boundaries of the cell center, whereas the cell face points are the endpoints of these cell faces. The cell face points at the outer boundary of the 2D flow area are used to connect the 2D flow area to other flow elements and boundary conditions.

In this study, the computational mesh was created in the HEC-RAS geometric data editor by specifying grid spacing in terms of DX and DY. Following Casulli (2009), a relatively coarser computational grid-cell spacing than the horizontal resolution of the underlying terrain (12.5 m) was used to improve the computation time. To determine the optimal grid-cell spacing, the model stability was evaluated via grid spacing values of 40 m, 50 m, and 60 m following studies by Costabile et al. (2020) and Psomiadis et al. (2020). Stability was assessed on the basis of the convergence of results and computational efficiency. The model was found to be stable with a grid-cell spacing of 50 m (DX = 50 m and DY = 50 m), which provided a good balance between accuracy and computation time. This resulted in the creation of 70,740 grid cells, with an average area of 2,512.64 m².

6.2.5.3 Boundary Conditions and Manning's Roughness Coefficient

The upstream boundary condition, which represents the point where flow enters the 2D flow area, was established at the Gumara Bridge, which is located at the Wanzaye stream gauging station (Figure 6.5). The downstream boundary condition, where flow exits, was set at the inlet of the Gumara River into Lake Tana.

In HEC-RAS 2D flood modeling, Manning's roughness coefficient (n) is a critical parameter influencing flow resistance and model accuracy. The latest version of HEC-RAS (6.5) supports importing LULC maps from various sources, facilitating the precise estimation of n values. In this study, the 2019 LULC map (Figure 6.5) was used to derive initial estimates of spatially varying n values. Using these LULC data, Manning's n values corresponding to different LULC classes were initially assigned on the basis of the recommendations of Chow (1959). Following the initial estimation of the n values, the optimal values were determined through model calibration.

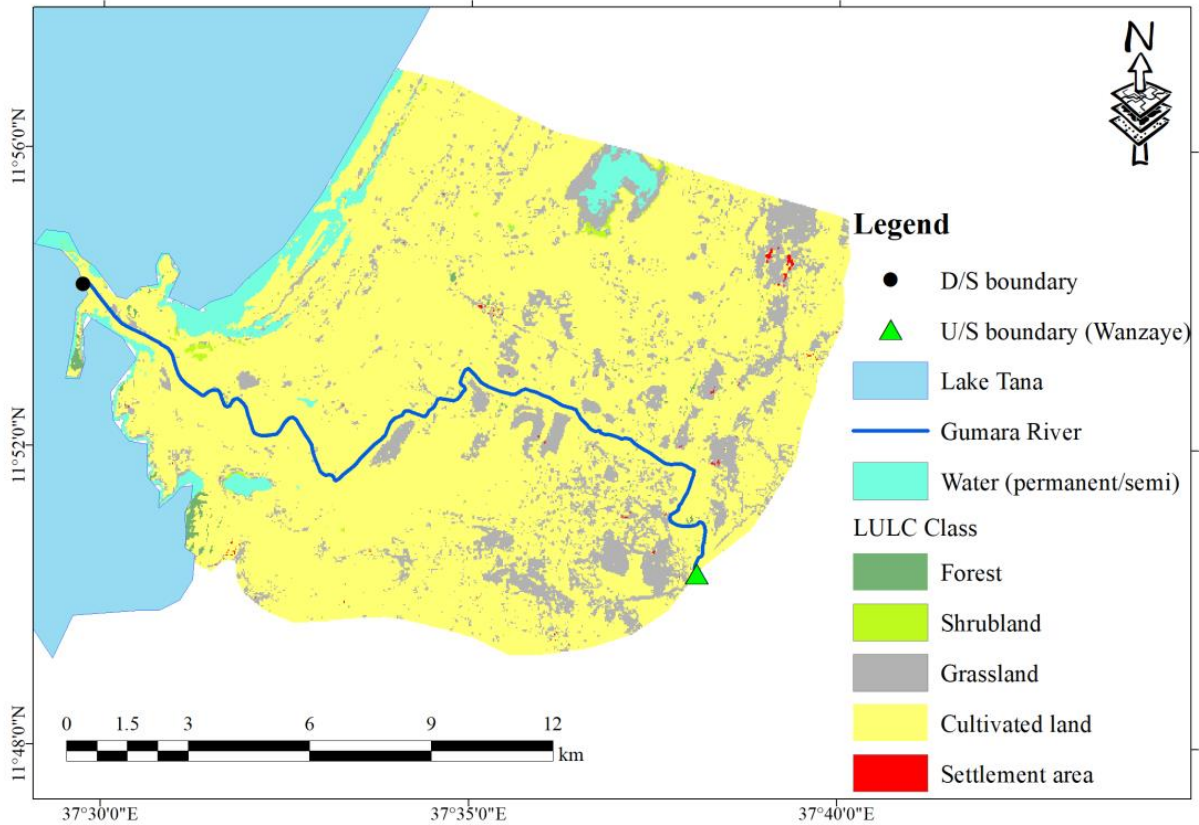


Figure 6.5. Boundary conditions and land use/land cover (LULC) map of the floodplain area for 2019. In the legend, the values indicated in brackets represent the ranges of Manning's n values corresponding to different LULC classes, as recommended by Chow (1959).

6.2.5.4 Unsteady Flow Analysis

Unsteady flow modeling in HEC-RAS 2D requires unsteady flow data for upstream and downstream boundary conditions. In this study, time series flow data from the Gumara River (July 21–August 31, 2019) were used as the upstream boundary conditions (Appendix C4). An average bed slope of 0.0012 was used as the downstream boundary condition for the Gumara River, corresponding to uniform (gradually varied) flow regime. Additionally, an initial water surface elevation (WSE) of 1785.5 m amsl was set to account for the water present in the river channel and permanent/semipermanent water bodies at the start of the simulation. Grid cells with elevations above this WSE were considered dry, whereas those below it were considered wet, with initial depths varying on the basis of terrain conditions.

In HEC-RAS 2D unsteady flood modeling, selecting an appropriate computational interval (Δt) is crucial for achieving accurate model outputs, including depth, water surface elevation, and velocity. It is also essential for ensuring model stability during flood simulation. Factors such as the mesh cell size

and flow velocity influence the determination of Δt . Among the various methods available, the Courant–Friedrichs–Lewy (CFL) condition (C. Hirsch, 1990) was employed in this study to determine Δt . In this method, to ensure model stability, the CFL condition is given as:

$$CFL = \frac{v\Delta t}{\Delta x} \leq 1; \quad (6.6)$$

Solving for Δt from equation (6.6) yields:

$$\Delta t = CFL \frac{\Delta x}{v} \quad (6.7)$$

where Δt is the computation interval (s), Δx is the mesh/grid cell size (m), v is the flood water velocity (m/s), and CFL is the Courant–Friedrichs–Lewy number, which is simply the Courant number.

6.2.5.5 Model Sensitivity Analysis

Sensitivity analysis is an essential step in evaluating how variations in input parameters influence model outputs (Tsubaki & Kawahara, 2013). It is typically measured as the positive or negative percentage change in model output relative to a reference scenario. In this study, the sensitivities of flood depth and inundation area were analyzed with respect to changes in Manning’s roughness coefficient (n). The analysis was performed by systematically increasing/decreasing the reference Manning’s n from -25% to 25% at 5% intervals following a similar procedure provided in Ghimire et al. (Ghimire et al., 2020). The resulting changes in flood depth and inundation area were computed relative to the results obtained via the baseline Manning’s n value. The baseline Manning’s n values were determined on the basis of the average of the upper and lower bounds provided for different land use and river channel types by Chow (1959). The percentage changes in flood depth and inundation area were calculated as follows:

$$\text{Change in depth (\%)} = \frac{Depth_{new} - Depth_{baseline}}{Depth_{baseline}} \quad (6.8)$$

$$\text{Change in area (\%)} = \frac{Area_{new} - Area_{baseline}}{A_{baseline}} \quad (6.9)$$

where $Depth_{new}$ and $Area_{new}$ represent the flood depth and inundation area computed via different Manning’s n values, respectively, whereas $Depth_{baseline}$ and $Area_{baseline}$ represent the flood depth and inundation area computed via the baseline Manning’s n value. In this study, model sensitivity Analysis Was Conducted For Flood Events That Occurred On August 5, 2019.

6.2.5.6 Model Calibration

In HEC-RAS 2D flood modeling, observed hydraulic data, including flood depth, water surface elevation, and flow velocity, are essential for calibration (Farooq et al., 2019; Ghimire et al., 2020).

However, in the absence of such data, several studies have recommended the use of flood inundation maps derived from remote sensing imagery, particularly from optical sensors and SAR sensors (Afzal et al., 2022; Ezzine et al., 2020; Madhuri et al., 2021). Among these, SAR-derived flood extent maps are widely used for calibrating HEC-RAS model parameters (Elkhrachy et al., 2021; Psomiadis et al., 2020). For this study, since observed hydraulic data were unavailable, the HEC-RAS model parameter, specifically Manning's roughness coefficient (n), was calibrated via SAR-derived flood extent maps from July 22, August 3, and August 27, 2019.

The calibration procedure involved several steps. First, initial Manning's n values were assigned for different land use types and river channels on the basis of published references. In this study, the average of the upper and lower bounds of Manning's roughness values for each land use type and river channel, as provided in Chow (1959), was assigned as the initial or baseline roughness value. Using these initially assigned n values, a flood simulation was performed, and the resulting flood map was compared with the SAR-derived flood map. The match between the simulated and SAR-derived flood maps was evaluated through visual inspection and the quantitative metrics described in Section 5.2.5.7.

Following the initial comparison, Manning's n value for each land use type and the river channel was gradually adjusted. The adjustment of Manning's n during calibration ranged from -25% to +25%, with intervals of 5%. The calibration was conducted manually by adjusting the roughness values of different land use types simultaneously. The optimal roughness values for each land use type were determined after 33 trial flood simulations were conducted (11 for each flood event). For this purpose, performance metrics were computed for each trial simulation of flood events (e.g., for the July 22, 2019 flood event). The Manning's roughness values that resulted in the highest performance scores were selected. The same procedure was followed for the flood events of August 3 and August 27, 2019. Finally, the calibrated Manning's n values were determined by averaging the optimal values obtained from the three events.

In addition to calibrating Manning's n values, a min-flow multiplier was applied to flow values lower than the mean flow, ensuring better agreement between the HEC-RAS model-simulated and SAR-based inundation maps. This approach involves computing the mean flow of the time series data or flow hydrograph and applying a multiplier only to flows below the mean while keeping higher flows unchanged. This is important for improving the numerical stability of the model and maintaining computational accuracy (Brunner, 2024b). For this purpose, min-flow multipliers ranging from 1.01 to 1.05 were tested with a 0.01 interval, and the best-performing value was selected to make slight min-flow adjustments.

6.2.5.7 Model Performance Evaluation

The performance of the HEC-RAS model during calibration was evaluated via performance metrics such as the F -score, overall accuracy (OA), and kappa coefficient (K). The F –score (Equation (6.10)) quantifies the model’s predictive ability, ranging from 0 to 1, with values approaching 1 indicating better performance in predicting flood extent. OA (Equation (6.11)) measures the agreement between HEC-RAS-modeled flood maps and SAR-derived flood maps, where values closer to 1 signify higher accuracy. K (Equation (6.12)) evaluates the level of agreement beyond chance between modeled and observed flooded pixels, ranging from -1 to 1, with values near 1 indicating strong agreement. These metrics were selected for their broad applicability in comparing model-simulated and SAR-derived inundation maps (Afzal et al., 2022; Akiyanova et al., 2023; Ezzine et al., 2020) and their ability to provide a comprehensive performance evaluation from multiple perspectives (Minh et al., 2024; Peng et al., 2025).

$$F - \text{score} = \frac{TP}{TP+FP+FN} \quad (6.10)$$

$$OA (\%) = \frac{TP+TN}{TP+FN+FP+TN} \quad (6.11)$$

$$K = \frac{P_o - P_e}{1 - P_e} \quad (6.12)$$

$$P_o = \frac{TP+TN}{T} \quad (6.13)$$

$$P_e = \frac{(TP+FP)*(TP+FN)+(TN+FP)*(TN+FN)}{T^2} \quad (6.14)$$

where TP (true positives) represents correctly predicted flooded pixels, TN (true negatives) represents correctly predicted nonflooded pixels, FP (false positives) represents pixels incorrectly predicted as flooded, and FN (false negatives) represents actual flooded pixels missed by the model. For the kappa coefficient (K), P_o is the observed agreement, P_e is the expected agreement, and T is the total number of pixels in the flood map, which is $(TP+FN+FP+TN)$.

6.2.5.8 Model Validation

To further validate the HEC-RAS model, GCPs for flooded and nonflooded areas were collected for the study area. These GCPs were obtained on the basis of Sentinel-2 multispectral optical imagery and field visit information from the areas most frequently affected by floods. Sentinel-2 imagery was selected because it is widely used in flood monitoring and the generation of validation points (Johary et al., 2023; Peng et al., 2025; L. Song et al., 2021). Additionally, floodwater can be easily detected because of its multispectral bands (Johary et al., 2023). For this study, the Sentinel-2 image from

August 30, 2019, was accessed via GEE and used for collecting the GCPs. Using this approach, 150 flooded and 150 nonflooded GCPs were collected and compared with the flood extent map of the HEC-RAS model.

Model performance was evaluated via key performance metrics, including OA , K , producer accuracy (PA), user accuracy (UA), omission error ($100 - PA$), and commission error ($100 - UA$). These metrics were chosen for their broad applicability in flood-related studies, as they evaluate performance from both the producer's and the user's perspectives (Johary et al., 2023; Peng et al., 2025; Song et al., 2021).

6.2.5.9 Flood Hazard Mapping

Flood hazard classification is important for assessing the potential impacts of flooding on different areas and plays a crucial role in supporting flood risk management strategies and enhancing emergency preparedness efforts (Madhuri et al., 2021). It involves categorizing areas according to key flood characteristics such as flood depth and velocity. In this context, several guidelines have been developed in different countries to classify flood hazards. The depth-velocity product (DVP) method of flood hazard classification was employed for this study on the basis of the UK Department for Environment, Food and Rural Affairs (DEFRA) guidelines (DEFRA, 2005) presented in Table 6.1.

Table 6.1. Depth–velocity product (DVP) method for flood hazard classification (DEFRA, 2005)

Hazard class	DVP (m^2/s) hazard rating
Low (H1)	$\text{DVP} < 0.75$
Moderate (H2)	$0.75 \leq \text{DVP} < 1.25$
Significant (H3)	$1.25 \leq \text{DVP} < 2.0$
Extreme (H4)	$\text{DVP} \geq 2.5$

6.2.5.10 Flood Inundation Mapping for Different Return Periods and Under Changing LULC and Climate Conditions

Flood inundation mapping for various return periods (5, 10, 25, 50, and 100 years) was conducted via the calibrated HEC-RAS model. In this analysis, inflow hydrographs (Figure 6.6a) computed via HEC-HMS from annual maximum 1-day rainfall data (1981–2019) were applied as upstream boundary conditions. These hydrographs were obtained from our recent work (Belay et al., 2025).

To examine the impacts of LULC and climate changes in the upstream Gumara watershed on downstream flood inundation, the HEC-RAS model was further run via inflow hydrographs representing extreme conditions (Figure 6.6b) sourced from our recent work (Belay et al., 2025). These hydrographs, derived from HEC-HMS simulations, were based on the ensemble means of four CMIP6 models. The simulations spanned historical (1981–2005), near-future (2031–2055), and far-future

(2056–2080) periods under the high-emission scenario SSP5–8.5 (Belay et al., 2025). In this analysis, historical LULC maps for 2000 and 2010 were used to represent baseline conditions, whereas projected LULC maps for 2035 and 2065 represented near-future and far-future scenarios, respectively. The integration of LULC and climate scenarios enabled the generation of inflow hydrographs that captured the combined impacts of these changes on flood inundation. This integrated approach provides valuable insights for flood management and planning in the Gumara watershed. Detailed methodologies for inflow hydrograph simulations across scenarios are provided in Belay et al. (2025).

The relative change in flood inundation extent between the historical and future periods was computed via the following equation:

$$\text{Relative Change (\%)} = \frac{A_{\text{future}} - A_{\text{historical}}}{A_{\text{historical}}} \times 100 \quad (6.15)$$

where $A_{\text{historical}}$ and A_{future} represent the total flood area (km²) during the historical and future periods, respectively.

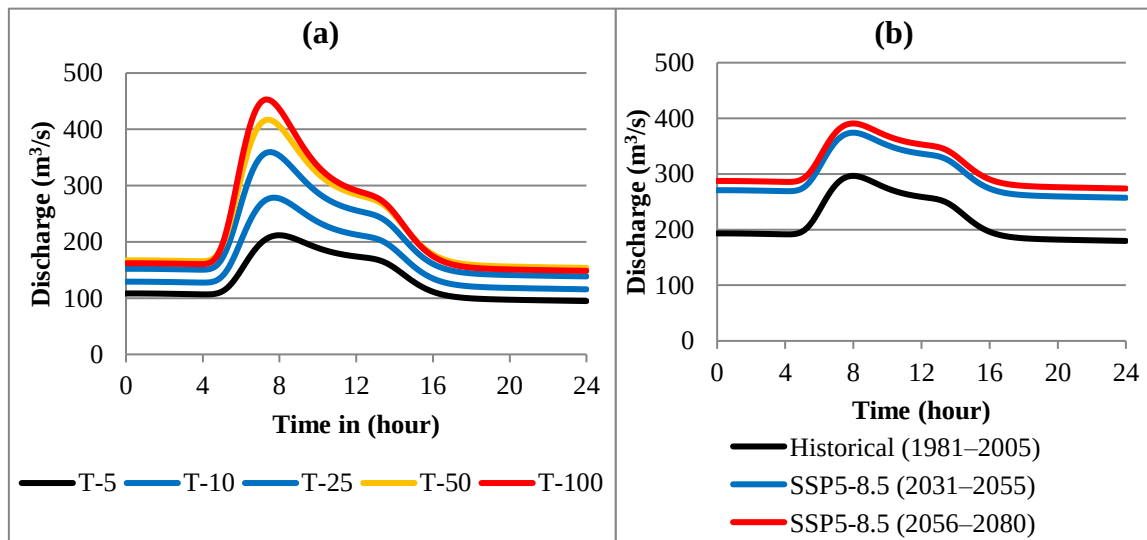


Figure 6.6. (a) Inflow hydrographs for different return periods (5, 10, 25, 50, and 100 years) and (b) inflow hydrographs for the extreme conditions of the historical (1981–2005), near-future (2031–2055), and far-future (2056–2080) periods, based on the SSP5-8.5 high-emission scenario.

6.3. Results

6.3.1 SAR-Based Flood Inundation Mapping

As described in the Methods section, SAR-based flood mapping was conducted via the GEE cloud-based platform following a change detection approach. The following subsections detail the characteristics of preflood and postflood images, the results of change detection and thresholding, and the refined flood inundation map generated through this method.

6.3.1.1 Pre- and Post-Flood SAR Images

Flood inundation mapping was conducted via SAR images acquired before and after the flood, as detailed in the methods section. The preflood images were acquired before the flood event and served as a reference, whereas the postflood images were acquired during or after the flood event and used to map areas inundated by floodwater. A composite of SAR images from January 11 and 23, 2019, was used to capture the preflood conditions of the area (Figure 6.7a). These images were selected because January is typically a dry month in the study area. SAR images for July 22, August 3, and August 27, 2019 (Figures 6.7b, c, & d, respectively) were used to delineate flood inundation on those dates. These specific images were chosen on the basis of the availability of SAR data for the given dates and to analyze the initiation, progression, and recession of floodwaters in the study area. All the images were processed through automated preprocessing steps in the GEE environment, and speckle filtering was applied via the Lee filter (Lee et al., 1994) to reduce noise (speckles) in the images.

In the SAR images (Figures 6.7b, c, & d), indicated with a red rectangle, the flooded areas appear dark due to low backscatter (σ^0) caused by specular reflection. In specular reflection, radar waves hitting smooth surfaces, such as water, are reflected away from the SAR sensor, resulting in few or no waves returning back to the sensor (Amitrano et al., 2024; Twele et al., 2016). This causes flooded areas to appear dark in SAR images. Conversely, nonflooded areas (such as dry land surfaces or vegetation covers) appear brighter in SAR images because of higher backscatter values, as these areas reflect more radar waves back to the sensor (Mason et al., 2009). On the other hand, permanent/semipermanent water bodies stored in wetlands and lake shores (indicated in the blue rectangle) remained unchanged before and after the flood (Figure 6.7a-d).

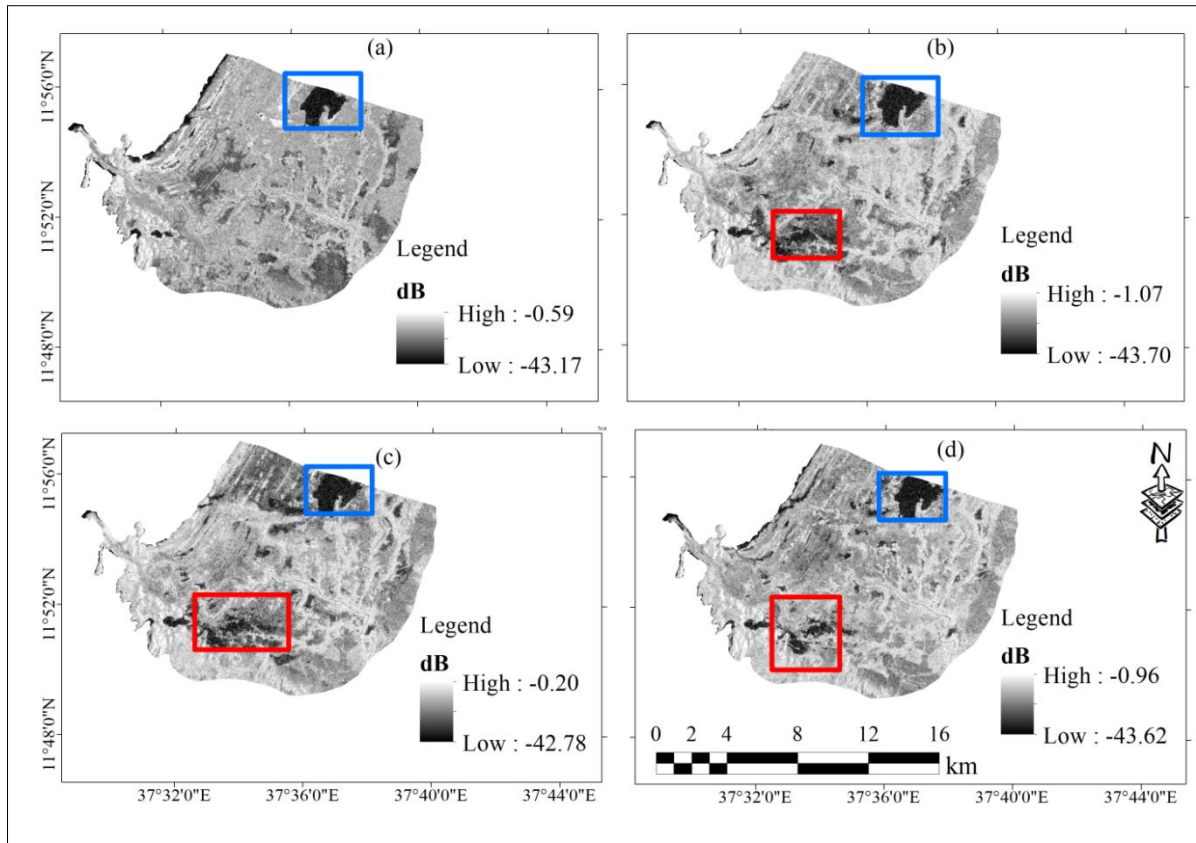


Figure 6.7. Preprocessed and speckle-filtered Sentinel-SAR images. (a) Before flood (composite image of January 11 and 23, 2019); (b) after flood (July 22, 2019); (c) after flood (August 3, 2019); and (d) after flood (August 27, 2019).

6.3.1.2 Change Detection and Thresholding

SAR-based flood inundation maps for the study area were generated by classifying the difference image into binary categories: flooded and nonflooded areas. Figures 6.8a–c show the pixel values of the difference image for the three flood events of 2019. In these figures, darker pixels indicate flooded areas with higher change magnitudes, whereas brighter pixels represent nonflooded areas with lower pixel values.

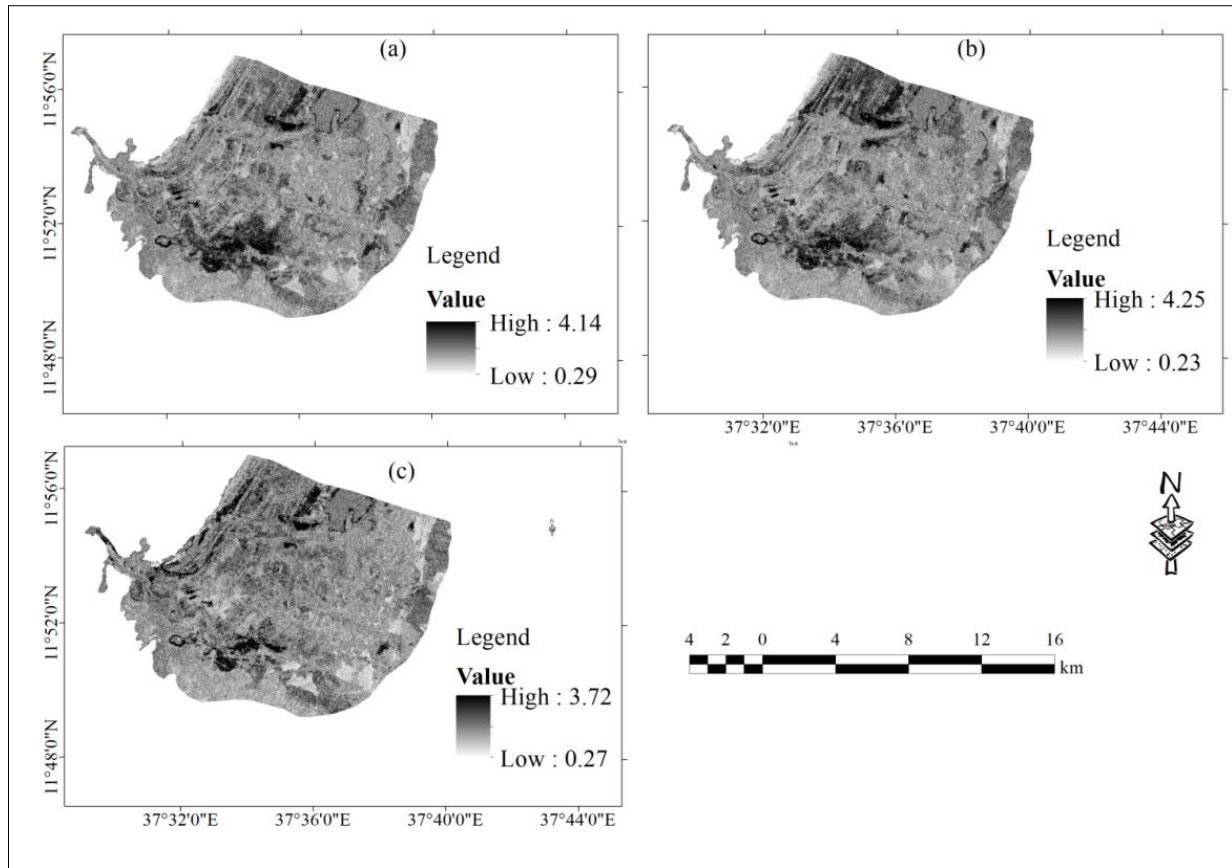


Figure 6.8. Difference images for the flood event of 2019: (a) July 22, 2019; (b) August 3, 2019); and (c) August 27, 2019.

Figures 6.9a–c illustrate the frequency distributions for three flood events in 2019, revealing a bimodal pattern with two distinct peaks. The transition zone between flooded and nonflooded pixels lies between 1.2 and 1.5. Among these, the threshold values of 1.30 and 1.40 were identified as optimal, corresponding to the lowest frequency (i.e., the valley) in the bimodal distribution. Specifically, a threshold of 1.30 was selected for the flood events on July 22 and August 3, 2019, whereas a threshold of 1.40 was chosen for the August 27, 2019 flood. Additionally, Figure 6.9d illustrates the percentage of flooded pixels for each event across threshold values from 1.10–1.50, revealing a decreasing trend in flooded pixels as the threshold increases.

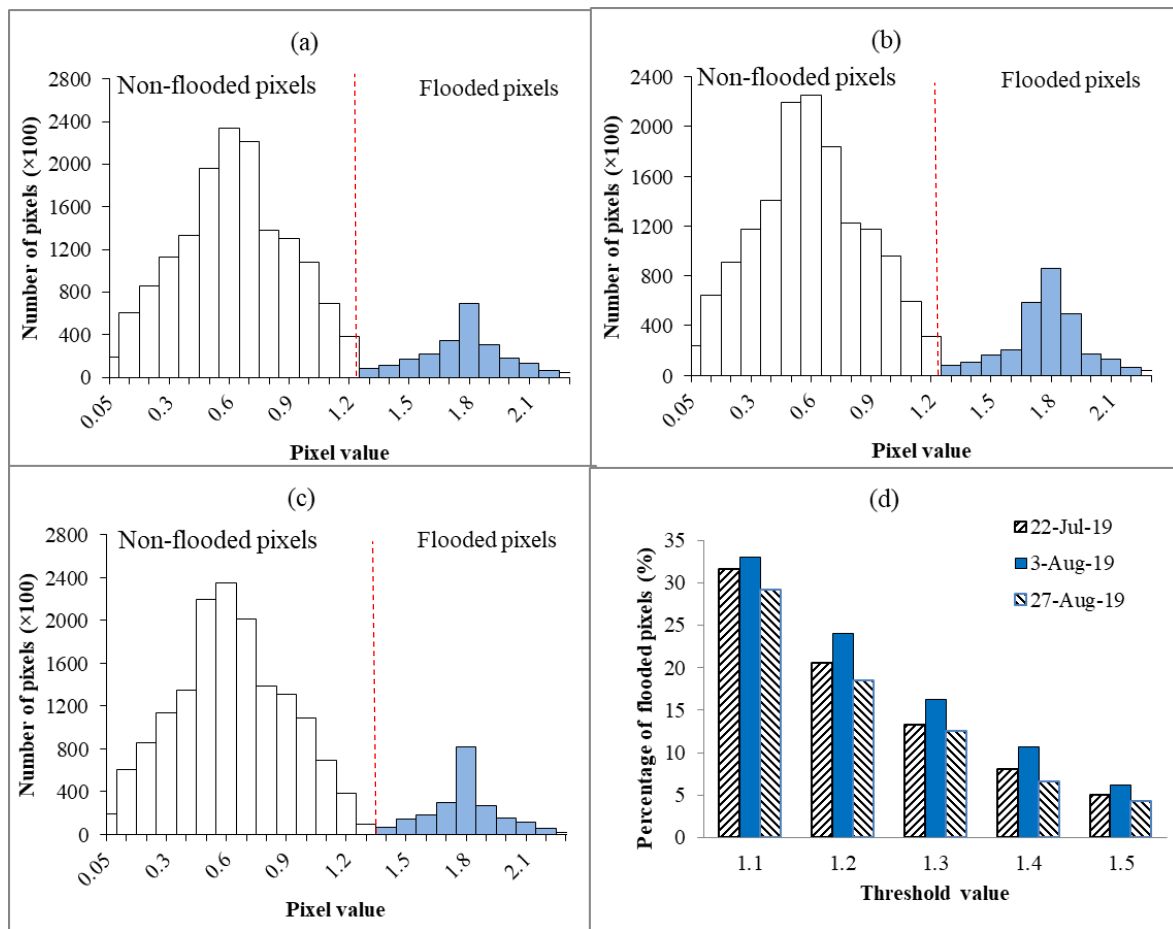


Figure 6.9. Frequency distributions (histograms) of flooded and nonflooded pixels in the difference image for three flood events: (a) July 22, 2019; (b) August 3, 2019; and (c) August 27, 2019; (d) percentage of flooded pixels for different threshold values. The red dashed line represents the threshold value used to separate flooded and nonflooded areas.

6.3.1.3 SAR-Based Flood Inundation Maps for 2019

To further refine the flood extent map generated via the change detection and thresholding approach, permanent/semipermanent water bodies, areas with slopes greater than 5%, and isolated or misclassified pixels were masked during the classification process, as detailed in the methods section. Figure 6.10 shows the refined flood inundation maps from July and August 2019. As illustrated in Figure 6.10a, flood inundation on July 22, 2019, was predominantly concentrated in the northern and southern parts of the flood-prone area, with a few isolated flood spots scattered across other regions. By August 3, 2019, as shown in Figure 6.10b, the flood had significantly progressed north and south. By August 27, 2019, as depicted in Figure 6.10c, the floodwaters had receded, especially in the southern and northern regions, with the remaining inundation confined primarily to depressions and wetlands.

For the study area, the flooded area was computed via the ARC-GIS. The results revealed that the inundated areas were 23.46 km², 28.86 km², and 22.26 km² on the three dates. This shows the initiation, expansion, and recession of the flood in the study area across these dates. In the study area, the distribution of floodwaters was influenced mainly by terrain conditions. The floodwater was concentrated along the course of the Gumara River, in low-lying areas (depressions), and in wetlands along the shoreline of Lake Tana, where the topography is nearly flat. Among the total flood-inundated area, more than 97% accounted for cultivated land, while the remaining area accounted for other land use classes.

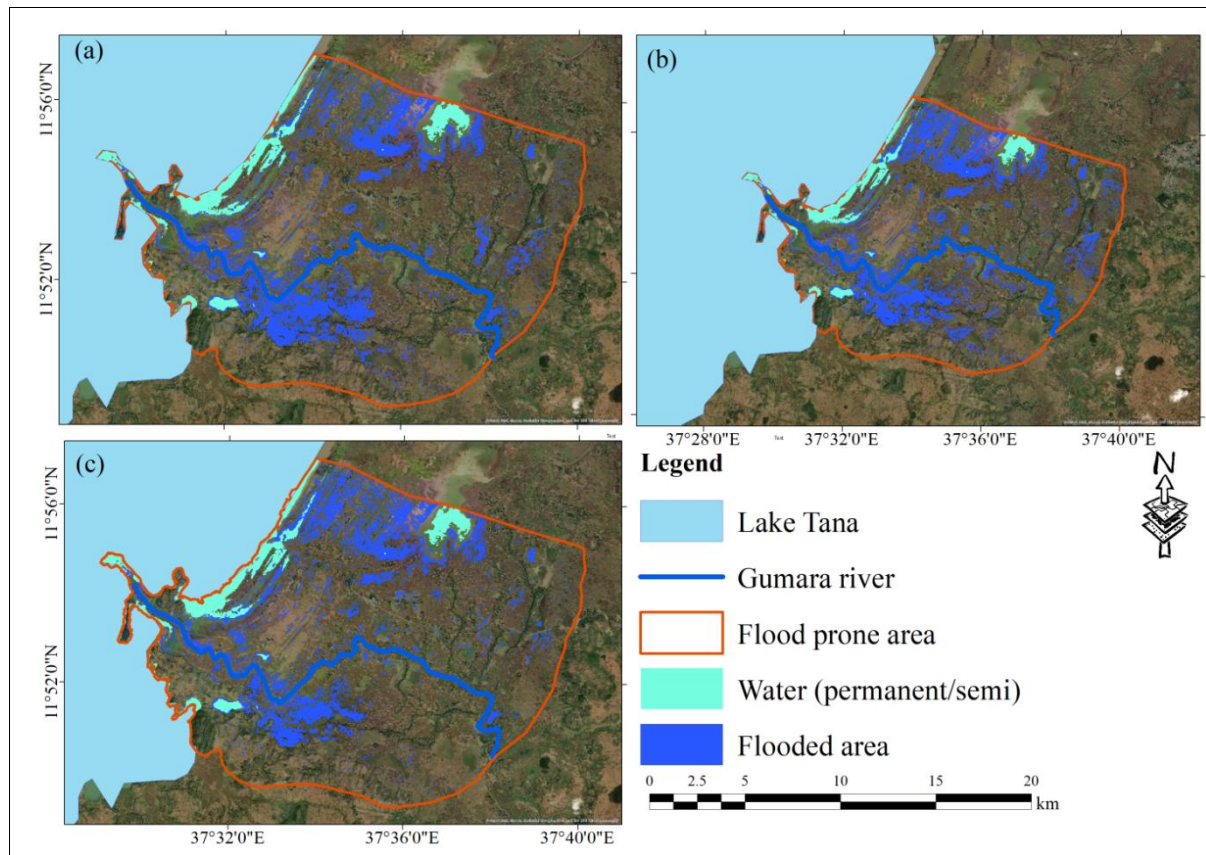


Figure 6.10. SAR-based flood inundation maps of the study area: (a) July 22, 2019; (b) August 03, 2019; and (c) August 27, 2019.

6.3.1.4 SAR-based flood frequency mapping

To assess the flooding conditions in the study area, flood frequency was analyzed via time series flood maps derived from Sentinel-1 SAR images over a five-year period (2017–2021). For each year, composite SAR images from January were used to represent preflood conditions, whereas composite images from July and August were used to capture postflood conditions. The resulting flood inundation maps for each year were then combined to determine flood frequency. Figures 6.11a–e present the time

series flood maps from 2017–2021, whereas Figure 6.11f displays the flood frequency over this period. As shown in the maps, flood frequency is highest near the meandering section of the Gumara River, highlighted within the red rectangle. Table 6.2 also provides the optimal threshold values used to distinguish flooded and nonflooded pixels, along with the corresponding flood extent for each year. According to the results, the highest flood inundation occurred in 2020, whereas the lowest flood inundation was observed in 2017.

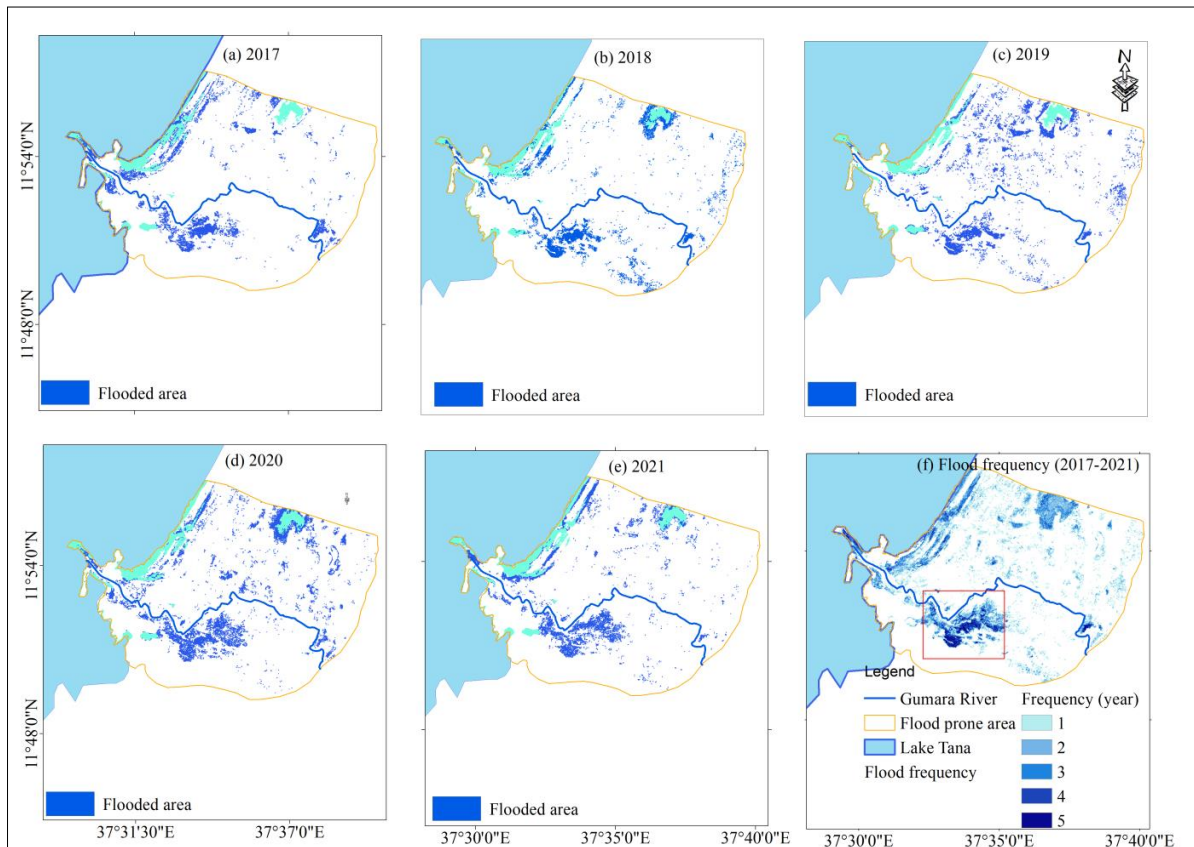


Figure 6.11. SAR-based time series inundation maps (2017–2019). Panels (a–e) show the inundation extent for different time periods, whereas panel (f) presents the flood frequency map. In panel (f), the dark blue areas within the red rectangle indicate frequently flood-affected regions.

Table 6. 2. Optimal threshold values and SAR-derived flood inundation areas from 2017–2021.

Year	Optimal threshold value	Flood inundation area (km ²)
2017	1.30	14.09
2018	1.25	11.22
2019	1.30	15.00
2020	1.34	21.15
2021	1.30	16.41
Average	1.32	15.57

6.3.2 Hydraulic Flood Modeling

The 2D unsteady flood simulation was conducted via the HEC-RAS model along a 26.56 km reach of the Gumara River, from Gumara Bridge at Wanzaye (upstream) to Lake Tana (downstream), encompassing the surrounding floodplain areas. To ensure model stability, a Courant-Friedrichs-Lew (CFL) value of 0.7 was employed, as recommended for flood simulations over flat floodplains (Brunner, 2024a). On the basis of the CFL value, a floodwater velocity of 1.2 m/s (typical for flat floodplain areas), and a mesh size of 50 meters, the computational time step was set to 30 seconds.

The simulation utilized time series streamflow data from July 20 to August 31, 2019, as the upstream boundary condition. On the basis of the simulation results, the flood event on August 5, 2019, was selected for model sensitivity analysis to change the HEC-RAS model parameters. The flood events on July 22, August 3, and August 27, 2019, were chosen for model calibration because they aligned with the Sentinel-1 SAR data. The flood event on August 30, 2019, was selected for validation because of the availability of a less cloudy Sentinel-2 image on this date, which was used to generate validation points for flooded and nonflooded areas.

6.3.2.1 Sensitivity Analysis

Figure 6.12a presents the sensitivity of flood depth to variations in Manning's n within a range of -25% to +25%. The results indicate a gradual increase in flood depth with increasing Manning's n values. This occurs because higher roughness increases resistance to flow, slowing the floodwater and causing greater accumulation (higher inundation depth) in the floodplain.

Similarly, Figure 6.12b illustrates the sensitivity of the flood inundation area to changes in Manning's n values. As with flood depth, the inundation area also expands with increasing roughness due to the increased frictional resistance, which slows floodwater movement, leading to greater water ponding and a broader flood extent. These findings align with previous studies that have demonstrated the sensitivity of flood depth and inundation area to changes in Manning's roughness n values (Dimitriadis et al., 2016; Ghimire et al., 2020).

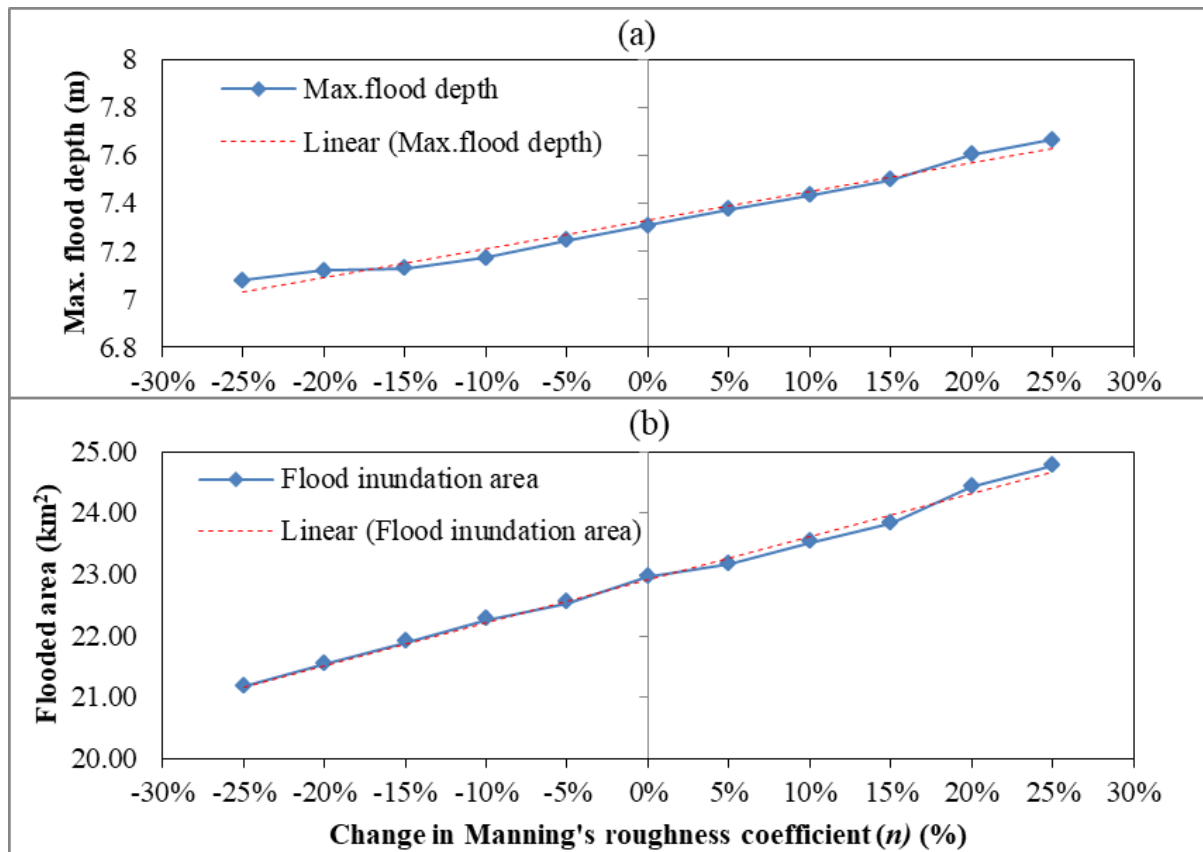


Figure 6.12. Sensitivity of (a) the maximum flood depth and (b) flood inundation area to changes in Manning's roughness coefficient (n) for the August 5, 2019 flood event.

The percentage change in flood depth and inundation area for different Manning's n values was computed relative to the baseline. The results revealed that negative changes in Manning's n led to negative changes in flood depth and area, whereas positive changes in Manning's n resulted in positive changes in both. Compared with the maximum flood depth, the flood inundation area exhibited greater sensitivity (Table 6.3). This higher sensitivity can be attributed to the relatively flat topography of the area, which enhances lateral expansion rather than vertical ponding when roughness conditions change (Tsubaki & Kawahara, 2013).

Table 6.3. Sensitivity of the maximum flood depth and inundation area to changes in Manning's roughness coefficient (n).

Change in Manning's roughness coefficient (n)	Maximum flood depth (m)	Change in maximum flood depth (%)	Flood inundation area (km ²)	Change in flooded area (%)
-25%	7.08	-3.13	21.17	-7.79
-20%	7.12	-2.59	21.53	-6.22
-15%	7.13	-2.46	21.89	-4.68
-10%	7.17	-1.87	22.26	-3.06
-5%	7.25	-0.85	22.54	-1.84
0% (baseline)	7.31	-	22.96	-
5%	7.38	0.91	23.17	0.88
10%	7.43	1.72	23.52	2.42
15%	7.50	2.58	23.84	3.80
20%	7.60	4.01	24.43	6.38
25%	7.66	4.87	24.77	7.86

6.3.2.2 Model Calibration

Manning's n value, a key parameter in the HEC-RAS model, was calibrated by comparing the computed flood inundation maps with the SAR-derived inundation maps. Initially, average Manning's n values for different land use types were assigned on the basis of Chow's recommendations (Chow, 1959) and were subsequently refined through iterative adjustments in 5% intervals, ranging from -25% to +25%. The iterative adjustment process involved modifying Manning's roughness coefficients simultaneously for all land use types in each simulation. While this approach requires multiple iterations (11 iterations for each flood event), it ensures that all possible values within the specified interval are considered.

Table 6.4 presents min, max, average (baseline), and calibrated Manning's n values for different land use types in the study area, listed in decreasing order of roughness values. According to the calibrated Manning's n values, the highest roughness value corresponds to forest ($n = 0.101$), whereas the lowest corresponds to water (permanent/semi) ($n = 0.015$). The river channel area ($n = 0.031$) has a greater roughness value than the settlement area ($n = 0.018$) because the river banks and channel areas of the Gumara River are vegetated, which can cause flow obstruction. In contrast, the settlement area is sparse, with open spaces, as it is dominated by rural settlements. On the other hand, cultivated land, which covers the largest area, ranked third in terms of roughness, with an n value of 0.040.

Additionally, among the tested min-flow multiplier values, which ranged from 1.01–1.05, a multiplier value of 1.02 was found to be optimal, improving the model's stability and maintaining computational accuracy.

Table 6. 4: Min, max, average, and calibrated Manning’s roughness n values for different land use types of the three flood events.

Land use/Land cover type	Manning's roughness n value						
	Min.	Max.	Average	Calibrated (Jul 22, 2019)	Calibrated (Aug 03, 2019)	Calibrated (Aug 27, 2019)	Calibrated (Average)
Forest	0.080	0.160	0.120	0.110	0.102	0.088	0.101
Shrubland	0.050	0.120	0.085	0.081	0.094	0.066	0.082
Cultivated land	0.030	0.060	0.045	0.044	0.045	0.031	0.040
Grassland	0.025	0.060	0.043	0.040	0.047	0.027	0.038
River channel area	0.025	0.045	0.035	0.030	0.034	0.026	0.031
settlement area	0.010	0.050	0.030	0.020	0.018	0.016	0.018
Water	0.010	0.020	0.015	0.013	0.017	0.015	0.015

6.3.2.3 Model Performance Evaluation

During the calibration process, the model's performance was evaluated via the $F - score$, OA , and K compared with those of the SAR-based flood inundation maps. The results revealed improvements in model performance, with $F - score$ increasing from 0.54 to 0.57, OA increasing from 85.66% to 86.92%, and K increasing from 0.59 to 0.62 from before calibration to after calibration (Table 6.5). This highlights the significance of calibrating Manning’s roughness in improving the model's accuracy. These findings align with those of previous studies that emphasized the critical role of roughness calibration in enhancing flood simulation performance (Ongdas et al., 2020; Quirogaa et al., 2016).

Table 6.5. Model performance metrics before and after calibration for the two flood events of 2019.

Flood event	Before calibration			After calibration		
	$F - score$	OA (%)	K	$F - score$	OA (%)	K
July 22, 2019	0.51	86.63	0.59	0.55	87.81	0.64
August 3, 2019	0.54	84.20	0.60	0.58	85.65	0.63
August 27, 2019	0.56	86.15	0.57	0.59	87.30	0.60
Average	0.54	85.66	0.59	0.57	86.92	0.62

6.2.4 HEC-RAS Model-Simulated Flood Inundation Maps

Using the calibrated Manning’s n values summarized in Table 6.5, the HEC-RAS model was run for three flood events in 2019 (Figure 6.13). The resulting maps illustrate the spatial extent of flood inundation depth on each date, showing variations in flood extent due to differences in inflow conditions. According to the maps, the computed floods were primarily concentrated along the banks of the main river and near the shores of Lake Tana.

The simulation results revealed that the maximum flood depths on July 22, August 3, and August 27, 2019, were 7.20 m, 7.32 m, and 7.26 m, respectively (Figures 6.13a-c). The corresponding average flood depths were 0.89 m, 0.96 m, and 0.86 m. The flood inundation areas for these three events were estimated to be 29.46 km², 33.28 km², and 31.48 km², respectively. These findings highlight the consistency of the maximum flood depth, average flood depth, and inundation area, with the highest values occurring on August 3, which coincided with the peak observed inflow. Additionally, the results align well with those of the SAR-based flood extent analysis, confirming that the maximum flood extent occurred on August 3. Overall, these findings demonstrate the suitability of the HEC-RAS model for simulating flood inundation in the study region.

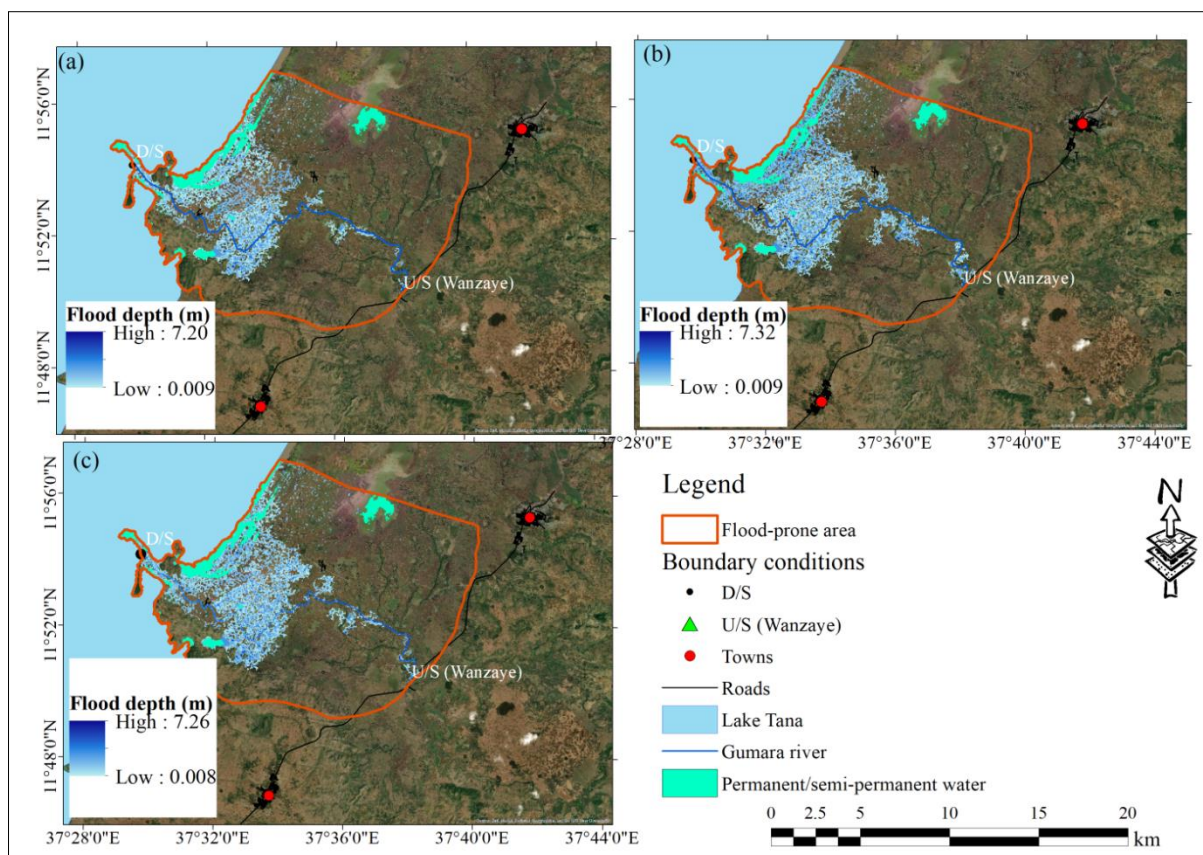


Figure 6.13. HEC-RAS model-computed flood inundation depth maps for (a) July 22, 2019; (b) August 3, 2019; and (c) August 27, 2019.

6.3.2.5 Model Validation

The HEC-RAS model flood inundation map was further validated via 300 ground control points (GCPs), comprising 150 points in flooded areas and 150 points in nonflooded areas. These GCPs were identified on the basis of Sentinel-2 imagery from August 30, 2019, and field investigations of frequently flood-affected areas, as described in the Methods section. Figures 6.14a and 14b illustrate

the HEC-RAS-derived flood inundation map and the spatial distributions of these GCPs used for model validation, respectively.

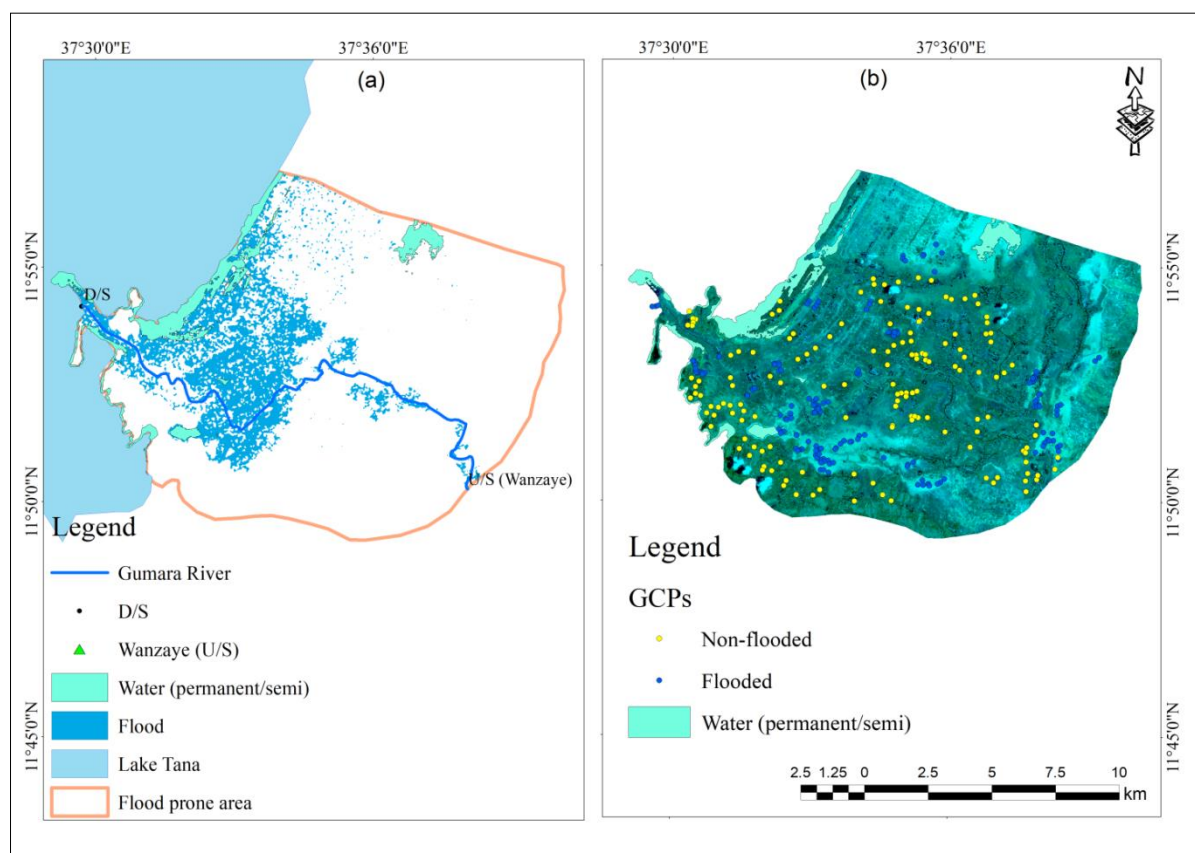


Figure 6.14. (a) HEC-RAS-derived flood inundation map for August 30, 2019. (b) Sentinel-2 satellite imagery for August 30, 2019, and ground control points (GCPs). The flood area GCPs are marked in blue, whereas the nonflooded area GCPs are shown in yellow.

The confusion matrix (Table 6.6) summarizes the model's accuracy compared with that of the GCPs. The *UA* for flooded pixels was 89.16%, indicating that 89.16% of the pixels classified as flooded were correctly identified, whereas 10.84% were misclassified (commission error). Similarly, the *UA* for nonflooded pixels was 82.84%, meaning that 17.16% of nonflooded pixels were misclassified. The *PA* for the flooded pixels was 86.55%, indicating that 86.05% of the actual flooded pixels were correctly classified, whereas 13.45% were omitted (omission error). Similarly, the *PA* for nonflooded pixels was 86.06%. Overall, the flood inundation maps generated via the HEC-RAS model demonstrated an *OA* of 86.33% and a *K* of 0.72, which can be considered substantial agreement according to Landis and Koch (Landis & Koch, 1977).

Table 6. 6. Confusion matrix for the validation of the HEC-RAS flood inundation map using ground control points (GCPs) and corresponding accuracy assessment results.

HEC-RAS	Ground control points (reference)			User's accuracy (%)	Commission error (%)
	Flooded	Non-Flooded	Σ		
Flooded	148	18	166	89.16	10.84
Nonflooded	23	111	134	82.84	17.16
Σ	171	129	300		
Producer's accuracy (%)	86.55	86.05			
Omission error (%)	13.45	13.95			
Overall accuracy (%)	86.33				
Kappa coefficient	0.72				

6.3.2.6 Flood Hazard Mapping

Flood hazard mapping is crucial for developing effective flood protection strategies and warning systems based on hazard levels. Depth and velocity are the most critical parameters in flood hazard mapping, as highlighted in several guidelines (DEFRA, 2005; FEMA, 2003). According to Brunner (Brunner, 2024b), these two factors are influenced primarily by elevation, surface roughness, and other floodplain characteristics.

In this study, the product of the computed depth (Figure 6.15a) and velocity (Figure 6.15b), termed the depth-velocity product (DVP), was used to classify flood hazard levels (H1 to H4) following the DEFRA (DEFRA, 2005) guidelines. The flood event on August 3, 2019, was selected for hazard classification, as it represented the most extreme condition among the three flood events analyzed. The resulting flood hazard map (Figure 6.15c) indicates an extreme hazard level (H4) along and near the Gumara River channel, characterized by higher DVP values ($DVP \geq 2.5$). In this area, the flood depth reached 7.32 m, and the flood velocity reached 1.58 m/s, leading to a relatively high DVP value. This extreme hazard level suggests severe flood damage in these areas. In contrast, the flatter parts of the floodplain presented varying hazard levels: low (H1), moderate (H2), and significant (H3). These findings align with those of previous studies by Anuthaman et al. (2023) and Costabile et al. (2020), who consistently reported extreme flood hazard levels along river channels and lower hazard levels in flatter floodplain regions. This pattern occurs because, during most flood events, water tends to accumulate in narrow river channels, leading to higher velocities due to the increased gravitational driving force (Brunner, 2024b). Conversely, in flatter floodplain areas with relatively uniform elevations, both depth and velocity decrease as the gravitational force decreases (Brunner, 2014, 2024b). Overall, the largest portion of the inundated area (approximately 45%) was categorized under the moderate hazard category (H2), whereas the smallest portion (approximately 8%) fell under the extreme hazard category (H4).

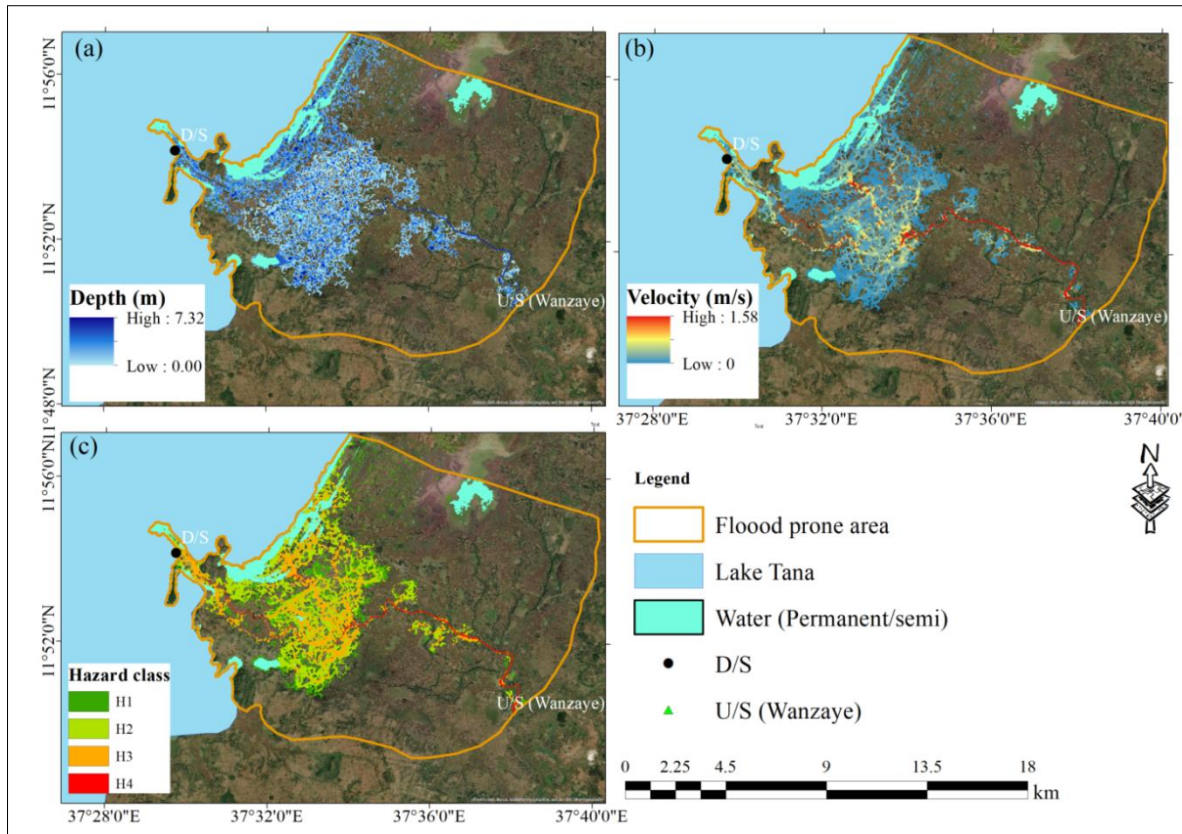


Figure 6.15. Flood depth, velocity, and hazard maps for the flood event of August 3, 2019: (a) computed flood depth (max=7.32 m), (b) computed flood velocity (max=1.58 m/s), and (c) flood hazard map. In (c), H1, H2, H3, and H4 represent low, moderate, significant, and extreme hazard levels, respectively, classified on the basis of the depth–velocity product (DVP).

6.3.2.7 Flood Inundation Maps under LULC and Climate Changes

Using the calibrated HEC-RAS model, flood simulations were conducted for different return periods (5, 10, 25, 50, and 100 years) via the inflow hydrographs presented in Figure 6.6a as the upstream boundary conditions. The resulting flood depth maps (Figure 6.16) revealed that areas near the Gumara River and along the shores of Lake Tana are particularly prone to flooding, with greater flood depths concentrated in these regions. In the computed maps, darker shades of blue indicate greater flood depths, whereas lighter shades of blue represent shallower flood depths. Overall, the simulations revealed average flood depths of 0.90, 0.92, 0.94, 0.97, and 1.02 m for the 5-, 10-, 25-, 50-, and 100-year return periods, respectively (Table 6.7).

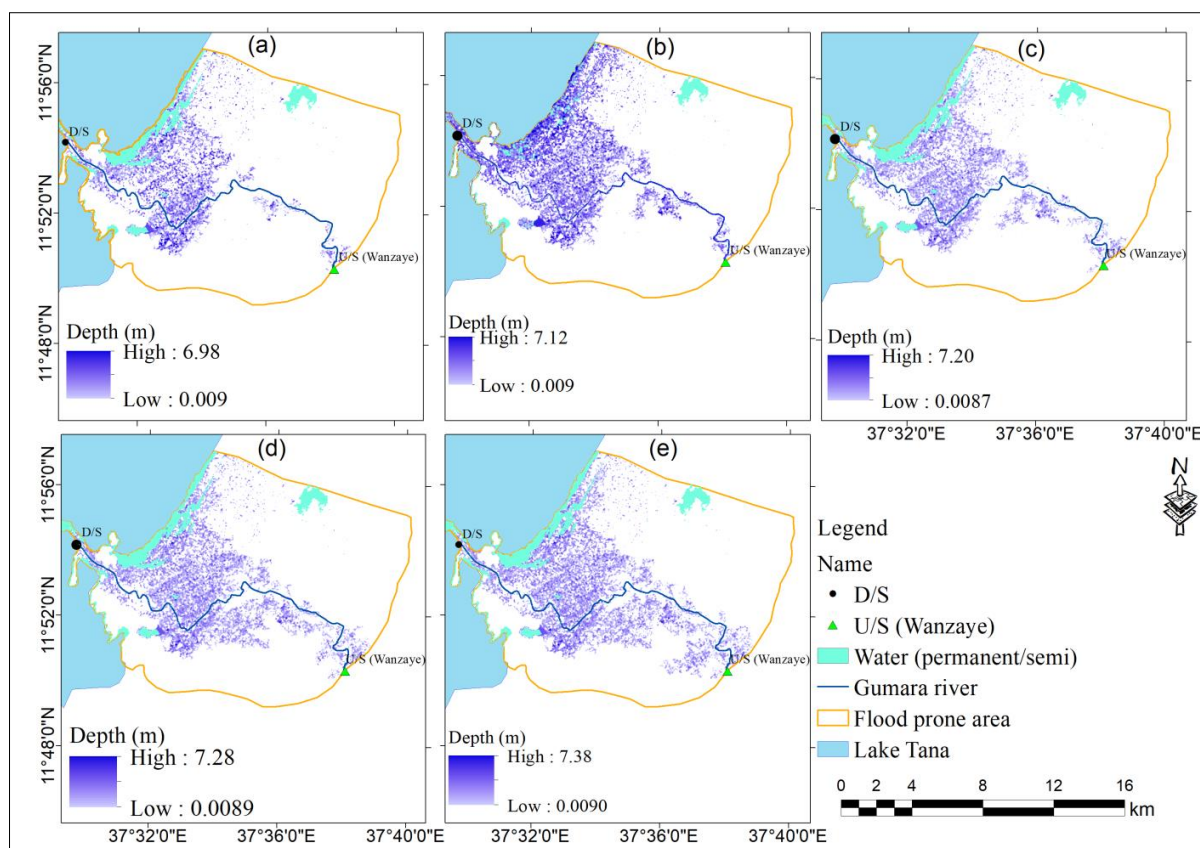


Figure 6.16. (a), (b), (c), (d), and (e) show flood inundation maps for different return periods for 5-, 10-, 25-, 50-, and 100-year return periods, respectively.

Table 6. 7. Flood inundation extent and depth for different return periods.

Return period (T)	Flooded area (km ²)	Flood depth (m)		
		Min	Max	Average
T-5	21.74	0.009	6.980	0.910
T-10	28.08	0.009	7.120	0.920
T-25	34.37	0.008	7.200	0.940
T-50	39.64	0.008	7.280	0.970
T-100	43.32	0.009	7.380	1.020

Similarly, via the calibrated HEC-RAS model, flood simulations were performed via the inflow hydrographs presented in Figure 6.6b as upstream boundary conditions for the historical and two future periods. Figure 6.17 shows the flood inundation maps generated for the historical (1981–2005), near-future (2031–2055), and far-future (2031–2055) periods under the SSP8.5 climate scenario. The results revealed a consistent positive change (increase) in both the flood extent and average flood depth in the two future periods (Table 6.8). According to the results, the flood inundation extent is expected to increase by 16.48% and 27.23% in the near future and far future periods, respectively, relative to the historical period. Similarly, increases in the average flood depth of 3.26% and 6.52% are expected in the near-future and far-future periods, respectively. This increase in flood inundation area and depth is

largely attributed to the greater magnitude of inflows expected in the future due to changes in LULC and climate conditions in the upstream watershed, as examined in our previous work (Belay et al., 2025). Consistent with these findings, a study by (Akter et al., 2018; Anuthaman et al., 2023; S. Yang et al., 2022) revealed an increase in flood occurrence under the combined effects of LULC and climate change.

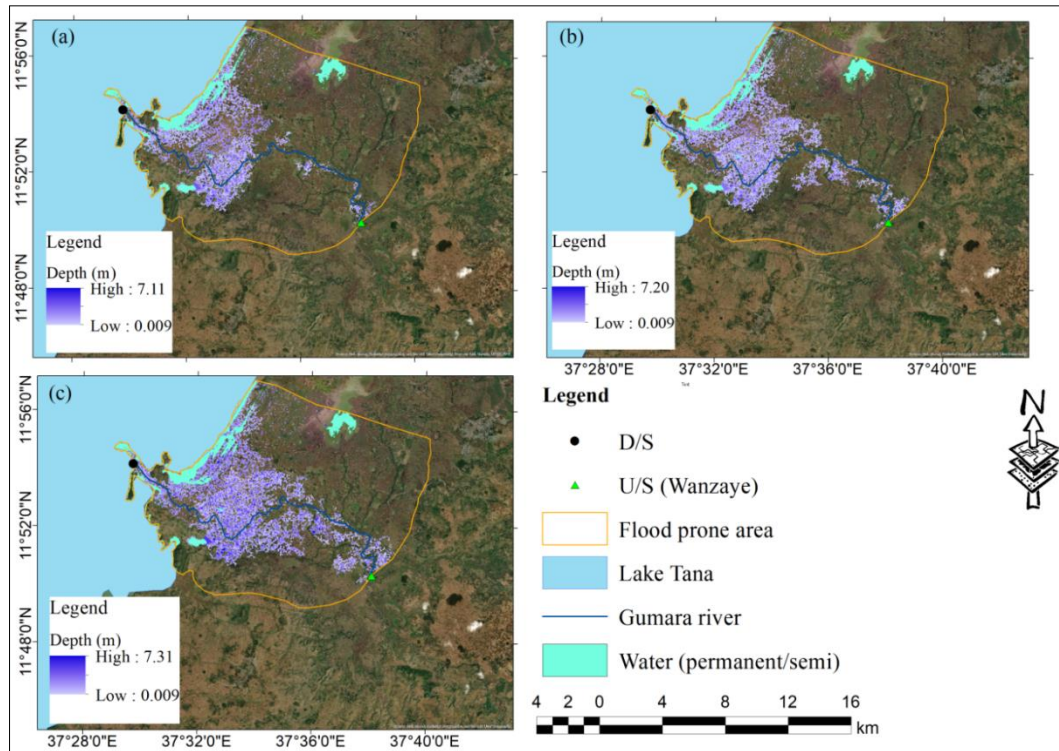


Figure 6. 17. (a) Flood inundation maps for the historical (1981–2005), (b) near-future (2031–2055), and (c) far-future (2055–2080) periods under the SSP5-8.5 climate scenario.

Table 6.8. Flood inundation extent and average flood depth and change analysis results between the historical and future periods.

Study period	Flood inundation area (km ²)	Change (%)	Average flood depth (m)	Change (%)
Historical (1981–2005)	28.09	–	0.92	–
SSP5-8.5 (2031–2055)	32.72	16.48	0.95	3.26
SSP5-8.5 (2056–2080)	35.74	27.23	0.98	6.52

6.3.3 Comparison of Flood Frequency Maps

To compare the flood inundation maps derived from SAR data and the HEC-RAS model, an overlay analysis was performed in ArcGIS for the 5-year return period. Figure 6.18 illustrates the flood extent captured exclusively by SAR data, exclusively by the HEC-RAS model, and their intersection. The results indicate that the overlapping area between both methods is larger than the flood extent captured by either method individually. The inundation analysis revealed that the average flood extent was 11.05

km² for SAR-derived only, 5.24 km² for HEC-RAS model-derived only, and approximately 16.60 km² for the intersection of both methods. As shown in Figure 6.18, the HEC-RAS model effectively captures flood inundation near the river and along the shores of Lake Tana. However, some flooded areas farther from the river were not captured by the HEC-RAS model. This discrepancy may be due to temporary water storage in depressions caused by excess rainfall rather than direct river overflow.

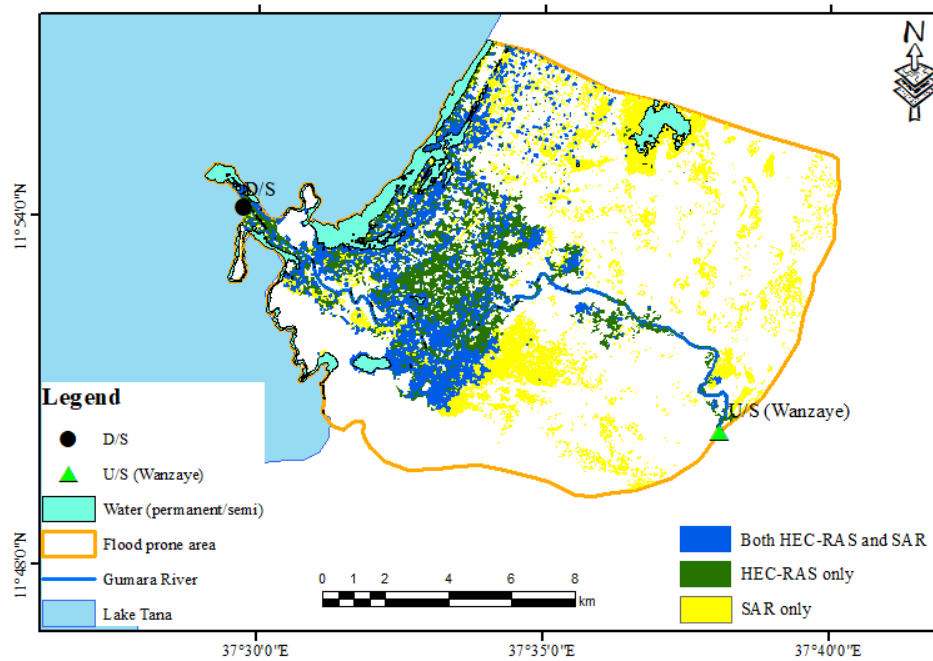


Figure 6.18. Comparison of flood inundation maps for the study area based on SAR and HEC-RAS for a 5-year return period.

6.4. Discussion

6.4.1 SAR-Derived Flood Inundation Mapping

Near-real-time SAR-based flood inundation maps were generated via a change detection approach on the GEE cloud-based platform for specific flood events in 2019, as were time series of inundation data from 2017–2021. Change detection is the most commonly used and recommended approach for SAR-based flood mapping (Huang & Jin, 2020; Li et al., 2018; Psomiadis et al., 2020; Zhao et al., 2018). This method is flexible and can be implemented on the GEE platform by setting a threshold value for the difference image, which distinguishes flooded areas from nonflooded areas. Since inundation mapping via change detection is sensitive to the threshold due to variations in image reflectance, different threshold values were determined for the time series flood inundation maps. In this study, optimal threshold values ranging from 1.25 to 1.40 were identified, which closely aligns with previous studies (Pandey et al., 2022; Singh & Rawat, 2024).

The SAR-derived flood inundation maps in this study adequately delineated frequently affected areas, which is consistent with the findings of a previous study conducted by Melkamu et al. (2022). However, a slight difference in the magnitude of the overall extent of the flood was observed. This can be attributed to differences in the timing of the SAR image acquisition, the floodplain area considered, and the flood detection algorithm used. Specifically, Melkamu et al. (2022) used SAR images acquired in July and August 2020, whereas this study utilized images from July and August 2019, along with composites from July to August, for time series inundation mapping. Additionally, Melkamu et al. (2022) considered floodplain areas frequently affected by both the Gumara and Rib Rivers, whereas this study focused only on areas affected by the overflow of the Gumara River. Furthermore, Melkamu et al. (2022) employed the Otsu thresholding algorithm (Otsu, 1975), whereas this study used a change detection approach. The Otsu thresholding method (Otsu, 1975) is mostly applied to classify single SAR images into flooded and nonflooded areas on the basis of backscatter intensity values. In contrast, the change detection approach compares preflood and postflood SAR images to identify areas where significant changes in backscatter intensity have occurred (Clement et al., 2018a). Therefore, change detection is often considered more flexible and robust, as it can track temporal changes rather than relying on intensity values from a single image (Giustarini et al., 2012; Tay et al., 2020; Tupas et al., 2023).

Despite the importance of Sentinel-1 SAR-derived flood inundation maps for near-real-time flood mapping in the absence of observed flood data, several limitations exist (Amitrano et al., 2024; Giustarini et al., 2012). For example, the acquisition of SAR images depends on satellite overpasses over specific areas, meaning that SAR sensors may miss fast or flash flood events due to their revisit times, which range from 6–12 days depending on the location. This limitation did not hinder the study, as the flood type in the Gumara watershed is characterized by riverine flooding, which typically has a longer progression and expansion time.

SAR sensors do not adequately capture floods under dense vegetation cover or urban areas with structures (Grimaldi et al., 2020; Tanim et al., 2022). In the Gumara watershed, more than 97% of the area is covered with cultivated land. Because of this, flood mapping was not hindered by this limitation of the SAR sensor. SAR images mostly suffer from speckle noise, which can affect the accuracy of flood mapping. In this study, this issue was addressed by applying the Lee speckle filter (Lee et al., 1994). Furthermore, while SAR-derived flood maps provide valuable information about flood extent, they do not directly provide information on flood depth or velocity. These parameters are important for detailed flood hazard mapping. To address the limitations of SAR-based flood inundation mapping, this study employed the HEC-RAS 2D model, which allows for a more comprehensive flood analysis

by simulating not only the extent but also the depth and velocity of floodwaters. This combination of SAR images and hydraulic modeling could improve the accuracy of flood risk mapping (Ezzine et al., 2020; Psomiadis et al., 2020).

6.4.2 HEC-RAS 2D Flood Modeling

In the HEC-RAS 2D model, the DW equations were chosen to compute flood depth and velocity over the 2D flow area. This method was selected because it does not demand high computational resources and has a shorter run time than the full SW equations perform (Brunner, 2024b; Costabile et al., 2020). Additionally, the DW approach provides high numerical stability and is well suited for simulating floods in relatively flat floodplain areas, such as the study area considered in this research (Ghimire et al., 2020; Nasiri et al., 2022).

The computed flood maps in HEC-RAS effectively delineated frequently affected areas, which is consistent with studies conducted by Melkamu et al. (Melkamu et al., 2022) and Nigusie et al. (Nigusie et al., 2021). However, slight differences were observed in the magnitude of flood depth and velocity. These variations could be attributed to differences in the flood-prone area considered, the terrain model resolution, the 2D computational mesh spacing, Manning's roughness n value, and other related parameters.

Unlike previous studies conducted in the area, this study incorporated a modified terrain model to account for flood propagation through the river channel and calibrated Manning's roughness n values to increase the accuracy of flood depth and velocity estimates. Additionally, the impacts of LULC and climate changes in the upland watershed were considered, and their influences on flood depth and flood extent in the floodplain for various return periods were examined. This was achieved by using inflow hydrographs computed under different LULC and climate conditions as upstream boundary conditions (Belay et al., 2025). The results revealed an increase in flood depth and extent in future periods, potentially intensifying the flood risk in the area. Similar studies have reported increases in flood depth and extent due to land use changes, such as deforestation, agricultural expansion, and urbanization, as well as extreme rainfall events (Q. Chen et al., 2020; Lane & Kay, 2021; Madhuri et al., 2021; Saghafian et al., 2008).

The HEC-RAS 2D model provides detailed information on flood dynamics but has several limitations. For example, the simulation time may be longer than that of SAR-derived flood inundation mapping because detailed topographic and hydraulic input data are needed (Ongdas et al., 2020; Quirogaa et al., 2016). To address this limitation, this study utilized a modified terrain model. Furthermore, while

HEC-RAS 2D simulation is primarily appropriate for smaller basins or watersheds, it may not be recommended for large-scale flood mapping.

In summary, despite their limitations, both the SAR-derived and HEC-RAS-computed flood inundation maps for the study area provide valuable information on the spatial and temporal distributions, extent, and progression of the flood. These maps can assist watershed managers, policymakers, environmentalists, and other stakeholders in developing early warning systems, designing sustainable flood protection and management strategies, and mitigating the impacts of flooding. Overall, to mitigate future flood risks in downstream areas, implementing sustainable land use practices, including reforestation and controlled agricultural cultivation, along with improved water management strategies to reduce the impact of extreme rainfall events on flooding, is recommended.

6.4.3. Future Research Directions

This study used Sentinel-1 SAR data for flood inundation mapping in the region. Future research could enhance flood mapping accuracy by incorporating multisource satellite imagery, such as Sentinel-2 and Landsat imagery, through a multisource data fusion approach.

The 2D hydrodynamic flood modeling in HEC-RAS in this study was performed via the DW equation, an approximation of the SW equation, owing to computational resource and data availability constraints. Future studies could explore the application of the full SW equation, utilize high-performance computing resources to account for acceleration in addition to primary governing forces (gravitational and friction forces), and compare the results with those obtained via the DW equation.

High-resolution elevation data are crucial for accurately estimating flood depths and velocities in flood modeling. In this study, a modified terrain DEM with a 12.5-meter resolution was used, as higher-resolution data for the area were not available. Future studies could benefit from incorporating high-resolution light detection and ranging (LiDAR) data to improve flood mapping in the region.

Additionally, further research on the socioeconomic impacts of flooding, along with the development and assessment of adaptive flood protection measures, is essential for enhancing resilience in flood-prone areas.

6.4. Conclusions

This study focused on generating near-real-time flood maps, flood inundation maps for different return periods, and future flood inundation scenarios for the downstream part of Gumara watershed. Near-real-time flood inundation mapping was conducted via Sentinel-1 SAR images on the GEE cloud-based platform for flood events that occurred from 2017–2021. Among these, flood events on July 22,

August 3, and August 27, 2019, were used to calibrate the HEC-RAS 2D model. SAR-based flood mapping was performed via a change detection approach followed by histogram thresholding of the difference image. The analysis revealed that the optimal threshold value for distinguishing flooded pixels ranged from 1.25–1.4.

A 2D hydraulic flood model was developed via HEC-RAS. Model sensitivity analysis was conducted by varying Manning's roughness coefficient (n), the primary parameter influencing 2D flood modeling. Model calibration was performed by comparing simulated flood maps with SAR-derived flood maps. Overall, considering the three calibration events, the model performance improved in terms of the F-score (from 0.54 to 0.57), OA (from 85.66% to 86.92%), and K (from 0.59 to 0.62). Further validation using ground control points (GCPs) resulted in an OA of 89.16% and a K of 0.72, indicating the model's effectiveness in simulating floods in the study region.

Using the calibrated model, flood inundation maps were generated for different return periods (5, 10, 25, 50, and 100 years). Additionally, future flood inundation scenarios were developed for the near-future and far-future periods. The results indicated a projected increase in the flood inundation area of 16.48% in the near future and 27.23% in the far future compared with the historical period. This increase is attributed to the combined effects of LULC changes and the intensification of extreme rainfall events due to climate change in the upstream watershed.

The flood inundation maps derived from SAR imagery and HEC-RAS modeling provide valuable information for watershed managers and decision-makers in designing effective flood risk mitigation structures. Future research could enhance flood mapping accuracy by integrating multisource satellite imagery, such as Sentinel-2 and Landsat imagery, through a data fusion approach. Additionally, applying the full SW equation in 2D hydrodynamic modeling, coupled with high-performance computing, could yield more detailed results than the DW approximation. The incorporation of high-resolution LiDAR data would improve flood depth and velocity estimates. Further studies should also focus on assessing the socioeconomic impacts of flooding and developing adaptive flood protection measures to increase resilience in flood-prone areas.

CHAPTER 7

7.1. Synthesis of the Overall Findings of the Study

This study provided evaluation of the combined impacts of LULC and climate changes on flood occurrence, source areas, and inundation extents in the Gumara watershed, part of the UBN basin,

Ethiopia. The motivation for this study stems from the recognition that climate change intensifies the frequency and magnitude of extreme rainfall events, while LULC changes reduce the watershed's capacity to absorb and convey surface runoff. The study employed a multidisciplinary methodological framework combining climate model evaluation, remote sensing, geospatial analysis, hydrological and hydraulic modeling, and flood inundation mapping. This section synthesizes the main findings across the chapters and discusses their broader implications for flood risk management.

The evaluation of 16 GCMs, comprising 8 CMIP5 and 8 CMIP6 models, demonstrated that both model generations were capable of reasonably simulating the observed ERFIs. However, the majority of CMIP6 models generally outperformed the CMIP5 models in reproducing the observed rainfall characteristics over the UBN basin. Future climate projections indicated an increase in the intensity and frequency of extreme rainfall events under high-emission scenarios (RCP8.5 and SSP5-8.5), highlighting an elevated flood risk driven by climate change. These findings underscore the importance of incorporating climate projections into regional flood risk assessments to enhance the reliability of future flood hazard evaluations.

Scenario-based LULC analysis demonstrated extensive conversion of forest, grasslands, and shrublands to cultivated land and settlements under the BAU scenario, whereas the governance GOV scenario, aligned with Ethiopia's GLI, showed the potential to mitigate such changes. LULC changes significantly influenced hydrological responses, as increased agricultural expansion and deforestation contributed to higher surface runoff and peak discharge. The study highlights that sustainable land management policies and afforestation/reforestation programs can reduce flood risks in future periods.

Flood source area identification using the UFR approach consistently highlighted specific subwatersheds, particularly W4 and W6, as major contributors to peak flood discharge at the main outlet under different land use conditions. This pattern is closely linked to the severity of LULC changes observed in these subwatersheds, where significant deforestation and agricultural expansion have increased surface runoff generation. These findings emphasize the spatial heterogeneity of flood contributions within the Gumara watershed and underscore the critical importance of prioritizing management interventions in these high-contributing areas. Moreover, the combined impact analysis revealed that both LULC and climate changes had a stronger influence on frequent flood events, emphasizing the compounded nature of these drivers. This underscores the need for integrated land management practices and climate adaptation strategies to mitigate flood risks under changing environmental conditions.

SAR-based flood inundation mapping and 2D hydraulic modeling using HEC-RAS provided robust estimates of historical and future flood extents. The near-future and far-future scenarios projected increases in inundation areas of 16.5% and 27.2%, respectively, driven by extreme rainfall intensification and upstream land cover alterations. These projections highlight the critical need for proactive floodplain management and infrastructure planning in downstream areas.

Overall, this study demonstrates the significant combined impacts of LULC and climate change on flood occurrence. The integrated modeling framework developed and applied in this study provides a scientific basis for developing adaptive watershed management strategies aimed at mitigating flood risks and enhancing the resilience of flood-prone regions under changing environmental conditions. The results provide actionable information for policymakers, watershed managers, and communities to implement sustainable land management and climate adaptation strategies aimed at reducing future flood risks.

7.2. Implications of the Study for Integrated Flood Risk Management

The findings highlight the urgent need for integrated flood risk management approaches that address both natural and human-induced drivers. Recommended actions include:

- Non-structural measures: floodplain zoning, watershed restoration, and early warning systems.
- Structural measures: flood embankments and improved drainage systems.
- Nature-based solutions: reforestation, afforestation, and controlled agricultural practices to restore the watershed's natural flood regulation functions.

The subwatershed-level flood source area analysis conducted in this study offers valuable insights for targeted watershed management and sustainable land use planning in the Gumara watershed. By identifying specific subwatersheds, particularly W4 and W6, as dominant contributors to peak flood discharge, the study highlights where intervention efforts should be concentrated to achieve the most significant flood mitigation efforts. Restoration of these degraded subwatersheds presents a critical opportunity to reduce flood magnitudes and restore the watershed's natural hydrological functions. Reforestation, soil and water conservation practices, and the rehabilitation of degraded landscapes in these subwatersheds can enhance infiltration, reduce surface runoff, and stabilize slopes, thereby moderating the watershed's hydrological response during heavy rainfall events.

Furthermore, the integration of flood risk assessments into watershed development plans is essential to ensure that future land use decisions do not exacerbate flood risks. Currently, the absence of spatially explicit flood hazard data in planning processes has led to maladaptive land use patterns. This study's

flood inundation maps and source area identification provide the spatial data necessary to guide zoning regulations and risk-sensitive land development strategies.

In summary, the findings of this study highlight the importance of proactive and spatially informed land use planning, grounded in scientific flood risk assessments and participatory watershed management. Such an integrated approach is vital for safeguarding the long-term sustainability and resilience of the Gumara watershed in the face of ongoing climate and land use pressures.

7.3. Methodological Contributions and Applicability

This study demonstrated the effectiveness of a multidisciplinary approach for integrated flood risk management. The combined use of satellite-based flood mapping and hydraulic modeling enhanced the accuracy of inundation extent predictions. Future climate projections under different scenarios, coupled with hydrological modeling, generated locally relevant design floods to support the design of flood protection structures. Additionally, the UFR approach facilitated the prioritization of critical subwatersheds for targeted flood mitigation. This integrated methodology can be applied to other watersheds with similar hydrological characteristics.

CHAPTER 8

8. Summary, Conclusions, and Recommendations

8.1. Summary

This study investigated the combined impacts of LULC and climate change on flood occurrence in the Gumara Watershed, UBN basin of Ethiopia. By integrating climate model evaluation, remote sensing, geospatial modelling, hydrological simulation, and hydrodynamic flood modelling, this study presented a comprehensive framework for understanding and managing flood risks under changing environmental conditions.

The study was structured around four key objectives: (1) evaluating and comparing the performance of the CMIP5 and CMIP6 GCMs in simulating ERFIs; (2) detecting historical and projecting future LULC changes via a random forest classifier and CA–Markov model; (3) assessing the combined effects of climate and LULC changes on flood frequency and flood source areas via the HEC-HMS model; and (4) mapping flood inundation extents via SAR data and HEC-RAS 2D hydrodynamic modelling.

Sixteen GCMs (eight from CMIP5 and eight from CMIP6) were evaluated for their performance in reproducing ERFIs for the baseline period (1981–2005) at the basin scale (UBN). Their performances were evaluated via statistical metrics (correlation coefficient, RMSE, and PBIAS) and ranked via the TOPSIS multicriteria decision-making approach. The top-ranked models were selected, bias corrected, and their ensembles were used to project future extremes under the RCP4.5, RCP8.5, SSP2–4.5, and SSP5–8.5 scenarios.

LULC classification was conducted for the years 1985, 2000, 2010, and 2019 via the RF algorithm via the GEE platform. Future LULC projections for 2035 and 2065 under the BAU and GOV scenarios revealed substantial expansion of agricultural and settlement areas under BAU, whereas the GOV scenario indicated a moderate increase in forest cover. The CA-Markov model effectively captured the spatial and temporal LULC transitions.

The hydrological response to combined LULC and climate changes was simulated via HEC-HMS. The results indicated a notable increase in peak flows under future conditions, with the most significant changes observed under the SSP5–8.5 climate scenario combined with the BAU-2065 scenario. FSAI, which is based on the UFR approach, highlighted subwatersheds W4 and W6 as the main contributors to peak flows, suggesting that these areas are priorities for flood mitigation interventions.

Flood inundation mapping was conducted via Sentinel-1 SAR imagery and processed via change detection algorithms on the GEE platform. These maps, covering the period 2017–2021, were used to calibrate and validate the HEC-RAS 2D hydraulic models, which were subsequently applied to simulate flood extent, depth, and hazard under both present and future scenarios. The results revealed substantial increases in flood extent, especially under the SSP5–8.5 and BAU-2065 combinations. Overall, this study provides valuable insights into flood risk dynamics and establishes a methodological framework for sustainable watershed management.

8.2. Conclusions

On the basis of the findings of this study, the following conclusions were synthesized:

- Sixteen GCMs (eight each from CMIP5 and CMIP6) were evaluated for reproducing observed ERFIs, with performance measured by correlation (R), RMSE, and PBIAS over the 1981–2005 period. The models were ranked via the TOPSIS method, with MIROC5, MRI-CGCM3, CanESM2, and MPI-ESM-LR (CMIP5) and MPI-ESM1-2-LR, MRI-ESM2-0, CNRM-CM6-1, and BCC-CSM2-MR (CMIP6) selected as the top performers. Bias-corrected ensembles of these models were used to project ERFIs under the RCP and SSP scenarios for 2031–2080. The results revealed positive changes in the CWD and RX5day under the high-emission scenarios (RCP8.5 and SSP5–8.5), with the other indices showing mixed trends and high variability.
- LULC classification for the years 1985–2019 revealed a consistent increase in cultivated and settlement areas, primarily at the expense of forest, shrubland, and grassland. With the CA–Markov model, future projections under the BAU scenario predict the continued conversion of natural landscapes into farmland and urban areas. In contrast, the GOV scenario, which assumes better land management and conservation efforts, demonstrated a moderate recovery of forested areas. These trends have direct implications for watershed hydrology and flood vulnerability.
- Rainfall–runoff simulations using the HEC-HMS model, under various combinations of future climate and land use scenarios, indicate a clear increase in annual maximum flow and peak discharge volumes. The most severe flooding is expected under the SSP5–8.5 climate scenario combined with the BAU-2065 land use scenario. FSAI, which is based on the UFR approach, indicated subwatersheds W4 and W6 as hotspots contributing disproportionately to high-flow events. These subwatersheds are recommended for priority consideration when interventions such as reforestation and water conservation measures are implemented.

- The extent of flood inundation is expected to expand under future climate and land use scenarios, as shown by the SAR-validated HEC-RAS simulations, highlighting increased downstream flood risks. By integrating SAR-based flood mapping from Sentinel-1 imagery with 2D hydraulic modelling in HEC-RAS, the study successfully simulated current and future flood extents. The model was calibrated and validated via observed flood events. Under future climate and LULC projections, especially SSP5–8.5 combined with the BAU-2065 scenario, flood extents in the downstream floodplain increased substantially. These results emphasize the urgent need for improved flood zoning, infrastructure planning, and early warning systems in vulnerable lowland areas.

8.3. Recommendations

The following recommendations are provided from the perspectives of land management, flood risk mitigation, policy and governance, replicability of the methodology, and future research directions:

- **Sustainable land use management:** This study suggests the promotion of afforestation, regulated agricultural expansion, and soil and water conservation, especially in subwatersheds W4 and W6, which have been identified as consistent flood source areas.
- **Integrated flood risk mitigation:** Developing early warning systems and flood control infrastructure in downstream areas prone to inundation, especially near agricultural lands and rural settlements, is recommended to reduce the adverse impacts of flooding in the study region.
- **Policy and governance measures:** This study recommends that local governments and policymakers promote the adoption of the GOV scenario, which emphasizes tree planting to mitigate the adverse impacts of land use and climate change on flooding. It also encourages collaboration among NGOs, community organizations, and stakeholders to strengthen watershed management programs.
- **Replicability of the methodology of the study:** The methodological framework presented in this study can be adapted for use in other regions with similar hydrological characteristics.
- **Applications of the findings of the study:** The generated flood inundation maps and return period-based flood estimates of this study can be valuable tools for land use planners, watershed managers, and investors. These stakeholders can use the information to make informed decisions, such as designing flood protection structures and avoiding flood-prone areas in the downstream parts of the Gumara watershed, thereby reducing flood risk for developments.

- **Future research directions:** Future research is encouraged to explore alternative climate model evaluation methods, such as envelope-based approaches, to complement the past-performance method used in this study. Enhancing LULC classification by incorporating texture features and updated population density data, once available, could improve future land cover projections. Further studies may also consider assessing the impacts of LULC changes on watershed hydrology and ecosystem services. In flood modelling, the integration of satellite-based soil moisture, multisource image fusion, high-resolution LiDAR, and full 2D hydrodynamic simulations could increase accuracy. Additionally, it would be valuable to investigate the backwater effect of Lake Tana on the adjacent floodplain areas and the socioeconomic effects of flooding.

References

- Abbas, S., Yaseen, M., Latif, Y., Waseem, M., Muhammad, S., Leta, M. K., Sher, S., Imran, M. A., Adnan, M., & Khan, T. H. (2022). Spatiotemporal Analysis of Climatic Extremes over the Upper Indus Basin, Pakistan. *Water*

- (Switzerland), 14(11). <https://doi.org/10.3390/w14111718>
- Abdi, A. M. (2020). Land cover and land use classification performance of machine learning algorithms in a boreal landscape using Sentinel-2 data. *GIScience and Remote Sensing*, 57(1), 1–20. <https://doi.org/10.1080/15481603.2019.1650447>
- Abdulkareem, J. H., Sulaiman, W. N. A., Pradhan, B., & Jamil, N. R. (2018). Relationship between design floods and land use land cover (LULC) changes in a tropical complex catchment. *Arabian Journal of Geosciences*, 11(14). <https://doi.org/10.1007/s12517-018-3702-4>
- Abida, K., Barbouchi, M., Boudabbous, K., Toukabri, W., Saad, K., Bousnina, H., & Sahli Chahed, T. (2022). Sentinel-2 Data for Land Use Mapping: Comparing Different Supervised Classifications in Semi-Arid Areas. *Agriculture (Switzerland)*, 12(9). <https://doi.org/10.3390/agriculture12091429>
- Abijith, D., & Saravanan, S. (2021). Assessment of Land Use And Land Cover Change Detection And Prediction Using Remote Sensing And CA Markov In The Northern Coastal Districts of Tamil Nadu, India Devanatham abijith National Institute of Technology Tiruchirappalli. *Research Square*, 1–26. <https://doi.org/10.21203/rs.3.rs-576976/v1>
- Abteu, W., Melesse, A. M., & Dessalegne, T. (2009). Spatial, inter and intra-annual variability of the Upper Blue Nile Basin rainfall. *Hydrological Processes: An International Journal*, 23(21), 3075–3082.
- Acharya, A., Lamb, K., & Piechota, T. C. (2013). Impacts of Climate Change on Extreme Precipitation Events Over Flamingo Tropicana Watershed. *Journal of the American Water Resources Association*, 49(2), 359–370. <https://doi.org/10.1111/jawr.12020>
- Acharya, N., Chattopadhyay, S., Mohanty, U. C., Dash, S. K., & Sahoo, L. N. (2013). On the bias correction of general circulation model output for Indian summer monsoon. *Meteorological Applications*, 20(3), 349–356.
- Adam, E., Mutanga, O., Odindi, J., & Abdel-Rahman, E. M. (2014). Land-use/cover classification in a heterogeneous coastal landscape using RapidEye imagery: evaluating the performance of random forest and support vector machines classifiers. *International Journal of Remote Sensing*, 35(10), 3440–3458. <https://doi.org/10.1080/01431161.2014.903435>
- Adane, G. B., Kassa, A. K., Toni, A. T., & Tekle, S. L. (2022). Spatial runoff estimation under different land uses and rainfall frequencies: case of flood-prone Dechatu River Catchment, Dire Dawa, Ethiopia. *Arabian Journal of Geosciences*, 15(11), 1092.
- Addisu, S., Selassie, Y. G., Fissaha, G., & Gedif, B. (2015). Time series trend analysis of temperature and rainfall in lake Tana Sub-basin, Ethiopia. *Environmental Systems Research*, 4(1). <https://doi.org/10.1186/s40068-015-0051-0>
- Afzal, M. A., Ali, S., Nazeer, A., Khan, M. I., Waqas, M. M., Aslam, R. A., Cheema, M. J. M., Nadeem, M., Saddique, N., Muzammil, M., & Shah, A. N. (2022). Flood Inundation Modeling by Integrating HEC–RAS and Satellite Imagery: A Case Study of the Indus River Basin. *Water (Switzerland)*, 14(19). <https://doi.org/10.3390/w14192984>
- Agidew, A. meta A., & Singh, K. N. (2017). The implications of land use and land cover changes for rural household food insecurity in the Northeastern highlands of Ethiopia: The case of the Teleyayen sub-watershed. *Agriculture and Food Security*, 6(1), 1–14. <https://doi.org/10.1186/s40066-017-0134-4>
- Akiyanova, F., Ongdas, N., Zinabdin, N., Karakulov, Y., Nazhbiyev, A., Mussagaliyeva, Z., & Atalikhova, A. (2023). Operation of Gate-Controlled Irrigation System Using HEC-RAS 2D for Spring Flood Hazard Reduction. *Computation*, 11(2), 1–23. <https://doi.org/10.3390/computation11020027>
- Aklile, Y., & Beyene, F. (2014). Examining drivers of land use change among pastoralists in Eastern Ethiopia. *Journal of Land Use Science*, 9(4), 402–413.
- Akter, T., Quevauviller, P., Eisenreich, S. J., & Vaes, G. (2018). Impacts of climate and land use changes on flood risk management for the Schijn River, Belgium. *Environmental Science and Policy*, 89(July), 163–175. <https://doi.org/10.1016/j.envsci.2018.07.002>
- Alaminie, A. A., Tilahun, S. A., Legesse, S. A., Zimale, F. A., Tarkegn, G. B., & Jury, M. R. (2021). Evaluation of past and future climate trends under CMIP6 scenarios for the UBNB (Abay), Ethiopia. *Water (Switzerland)*, 13(15). <https://doi.org/10.3390/w13152110>
- Aldiansyah, S., Saputra, R. A., Wahid, K. A., Madani, I., & Setiyo, D. (2024). Rapid Flood Inundation Mapping Using Multi-Temporal Sentinel-1 SAR: An Example from Kendari City. *Jurnal Geosains Dan Remote Sensing*, May. <https://doi.org/10.23960/jgrs.ft.unila.205>
- Alehu, B. A., Desta, H. B., & Daba, B. I. (2022). Assessment of climate change impact on hydro-climatic variables and its trends over Gidabo Watershed. *Modeling Earth Systems and Environment*, 8(3), 3769–3791. <https://doi.org/10.1007/s40808-021-01327-w>
- Alemayehu, A., Maru, M., Bewket, W., & Assen, M. (2020). Spatiotemporal variability and trends in rainfall and temperature in Alwero watershed, western Ethiopia. *Environmental Systems Research*, 9(1). <https://doi.org/10.1186/s40068-020-00184-3>
- Alemu, D., & Assaye, A. (2020). Devastating effect of floods on rice production and commercialisation in the Fogera plain. *Future Agriculture Consortium*, ii.
- Ali Mohammed, J., Gashaw, T., Worku Tefera, G., Dile, Y. T., Worqlul, A. W., & Addisu, S. (2022). Changes in observed rainfall and temperature extremes in the Upper Blue Nile Basin of Ethiopia. *Weather and Climate*

- Extremes*, 37(May), 100468. <https://doi.org/10.1016/j.wace.2022.100468>
- Almazroui, M., Saeed, F., Saeed, S., Ismail, M., Ehsan, M. A., Islam, M. N., Abid, M. A., O'Brien, E., Kamil, S., Rashid, I. U., & Nadeem, I. (2021). Projected Changes in Climate Extremes Using CMIP6 Simulations Over SREX Regions. *Earth Systems and Environment*, 5(3), 481–497. <https://doi.org/10.1007/s41748-021-00250-5>
- Almazroui, M., Saeed, F., Saeed, S., Nazrul Islam, M., Ismail, M., Klutse, N. A. B., & Siddiqui, M. H. (2020). Projected Change in Temperature and Precipitation Over Africa from CMIP6. *Earth Systems and Environment*, 4(3), 455–475. <https://doi.org/10.1007/s41748-020-00161-x>
- Althor, G., Watson, J. E. M., & Fuller, R. A. (2016). Global mismatch between greenhouse gas emissions and the burden of climate change. *Scientific Reports*, 6, 1–6. <https://doi.org/10.1038/srep20281>
- Amini, S., Saber, M., Rabiei-Dastjerdi, H., & Homayouni, S. (2022). Urban Land Use and Land Cover Change Analysis Using Random Forest Classification of Landsat Time Series. *Remote Sensing*, 14(11), 1–23. <https://doi.org/10.3390/rs14112654>
- Amitrano, D., Di Martino, G., Di Simone, A., & Imperatore, P. (2024). Flood Detection with SAR: A Review of Techniques and Datasets. *Remote Sensing*, 16(4), 1–38. <https://doi.org/10.3390/rs16040656>
- Amsalu, T., & Addisu, S. (2014). Assessment of Grazing Land and Livestock Feed Balance in Gummara-Rib Watershed, Ethiopia. *Current Agriculture Research Journal*, 2(2), 114–122. <https://doi.org/10.12944/carj.2.2.08>
- Anderson, T. W., & Darling, D. A. (1952). Asymptotic theory of certain "goodness of fit" criteria based on stochastic processes. *The Annals of Mathematical Statistics*, 193–212.
- Animashaun, I. M., Oguntunde, P. G., Akinwumiju, A. S., & Olubango, O. O. (2020). Rainfall analysis over the Niger central hydrological area, Nigeria: Variability, trend, and change point detection. *Scientific African*, 8, e00419.
- Anteneh, M., & Mohammed, W. (2020). Effects of land cover changes and slope gradient on soil quality in the Gumara watershed, Lake Tana basin of North – West Ethiopia. *Modeling Earth Systems and Environment*, 6(1), 85–97. <https://doi.org/10.1007/s40808-019-00660-5>
- Anusha, N., & Bharathi, B. (2020). Flood detection and flood mapping using multi-temporal synthetic aperture radar and optical data. *The Egyptian Journal of Remote Sensing and Space Science*, 23(2), 207–219.
- Anuthaman, S. N., Ramasamy, S., Lakshminarayanan, B., & Ramasubbu, B. (2023). Modelling and forecasting of urban flood under changing climate and land use land cover. *Journal of Water and Climate Change*, 14(12), 4314–4335. <https://doi.org/10.2166/wcc.2023.164>
- Arfasa, G. F., Owusu-Sekyere, E., & Doke, D. A. (2023). Predictions of land use/land cover change, drivers, and their implications on water availability for irrigation in the Veia catchment, Ghana. *Geocarto International*, 38(1). <https://doi.org/10.1080/10106049.2023.2243093>
- Argaz, A., Ouahman, B., Darkaoui, A., Bikhtar, H., Ayouch, E., & Lazaar, R. (2019). Flood Hazard Mapping Using remote sensing and GIS Tools: A case study of Souss Watershed. *J. Mater. Environ. Sci*, 10(2), 170–181.
- Asif, M., Kazmi, J. H., Tariq, A., Zhao, N., Guluzade, R., Soufan, W., Almutairi, K. F., Sabagh, A. El, & Aslam, M. (2023). Modelling of land use and land cover changes and prediction using CA-Markov and Random Forest. *Geocarto International*, 38(1). <https://doi.org/10.1080/10106049.2023.2210532>
- Awulachew, S. B., McCartney, M., Steenhuis, T. S., & Ahmed, A. A. (2009). *A review of hydrology, sediment and water resource use in the Blue Nile Basin*.
- Ayalew, D. W., Asefa, T., Moges, M. A., & Leyew, S. M. (2022). Evaluating the potential impact of climate change on the hydrology of Ribb catchment, Lake Tana Basin, Ethiopia. *Journal of Water and Climate Change*, 13(1), 190–205. <https://doi.org/10.2166/wcc.2021.049>
- Ayehu, G. T., Tadesse, T., & Gessesse, B. (2021). Spatial and temporal trends and variability of rainfall using long-term satellite product over the Upper Blue Nile Basin in Ethiopia. *Remote Sensing in Earth Systems Sciences*, 4(3), 199–215.
- Ayehu, G. T., Tadesse, T., Gessesse, B., & Dinku, T. (2018). Validation of new satellite rainfall products over the Upper Blue Nile Basin, Ethiopia. *Atmospheric Measurement Techniques*, 11(4), 1921–1936. <https://doi.org/10.5194/amt-11-1921-2018>
- Baez-Villanueva, O. M., Zambrano-Bigiarini, M., Beck, H. E., McNamara, I., Ribbe, L., Nauditt, A., Birkel, C., Verbist, K., Giraldo-Osorio, J. D., & Xuan Thinh, N. (2020). RF-MEP: A novel Random Forest method for merging gridded precipitation products and ground-based measurements. *Remote Sensing of Environment*, 239(January), 111606. <https://doi.org/10.1016/j.rse.2019.111606>
- Baghel, T., Babel, M. S., Shrestha, S., Salin, K. R., Virdis, S. G. P., & Shinde, V. R. (2022). A generalized methodology for ranking climate models based on climate indices for sector-specific studies: An application to the Mekong sub-basin. *Science of the Total Environment*, 829, 154551. <https://doi.org/10.1016/j.scitotenv.2022.154551>
- Baky, M. A. Al, Islam, M., & Paul, S. (2020). Flood Hazard, Vulnerability and Risk Assessment for Different Land Use Classes Using a Flow Model. *Earth Systems and Environment*, 4(1), 225–244. <https://doi.org/10.1007/s41748-019-00141-w>
- Bastola, S., & François, D. (2012). Temporal extension of meteorological records for hydrological modelling of Lake Chad Basin (Africa) using satellite rainfall data and reanalysis datasets. *Meteorological Applications*, 19(1), 54–70. <https://doi.org/10.1002/met.257>

- Beck, H. E., Vergopolan, N., Pan, M., Levizzani, V., Van Dijk, A. I. J. M., Weedon, G. P., Brocca, L., Pappenberger, F., Huffman, G. J., & Wood, E. F. (2017). Global-scale evaluation of 22 precipitation datasets using gauge observations and hydrological modeling. *Hydrology and Earth System Sciences*, 21(12), 6201–6217. <https://doi.org/10.5194/hess-21-6201-2017>
- Belay, H., Melesse, A. M., & Tegegne, G. (2022). Merging Satellite Products and Rain-Gauge Observations to Improve Hydrological Simulation: A Review. *Earth*, 3(4), 1275–1289.
- Belay, H., Melesse, A. M., & Tegegne, G. (2024a). Evaluation and comparison of the performances of the CMIP5 and CMIP6 models in reproducing extreme rainfall in the Upper Blue Nile basin of Ethiopia. *Theoretical and Applied Climatology*, 2019. <https://doi.org/10.1007/s00704-024-05187-z>
- Belay, H., Melesse, A. M., & Tegegne, G. (2024b). Scenario-Based Land Use and Land Cover Change Detection and Prediction Using the Cellular Automata–Markov Model in the Gumara Watershed, Upper Blue Nile Basin, Ethiopia. *Land*, 13(3). <https://doi.org/10.3390/land13030396>
- Belay, H., Melesse, A. M., & Tegegne, G. (2024c). Scenario-Based Land Use and Land Cover Change Detection and Prediction Using the Cellular Automata–Markov Model in the Gumara Watershed, Upper Blue Nile Basin, Ethiopia. *Land*, 13(3), 396.
- Belay, H., Melesse, A. M., & Tegegne, G. (2025). *Identifying Flood Source Areas and Analyzing High-Flow Extremes Under Changing Land Use , Land Cover , and Climate in the Gumara Watershed , Upper Blue Nile Basin , Ethiopia*.
- Benyahya, L., Gachon, P., St-Hilaire, A., & Laprise, R. (2014). Frequency analysis of seasonal Extreme precipitation in southern Quebec (Canada): An evaluation of regional climate model simulation with respect to two gridded datasets. *Hydrology Research*, 45(1), 115–133. <https://doi.org/10.2166/nh.2013.066>
- Berhane, A., Hadgu, G., Worku, W., & Abrha, B. (2020). Trends in extreme temperature and rainfall indices in the semi-arid areas of Western Tigray, Ethiopia. *Environmental Systems Research*, 9(1). <https://doi.org/10.1186/s40068-020-00165-6>
- Berihun, M. L., Tsunekawa, A., Haregeweyn, N., Meshesha, D. T., Adgo, E., Tsubo, M., Masunaga, T., Fenta, A. A., Sultan, D., & Yibeltal, M. (2019a). Exploring land use/land cover changes, drivers and their implications in contrasting agro-ecological environments of Ethiopia. *Land Use Policy*, 87(May). <https://doi.org/10.1016/j.landusepol.2019.104052>
- Berihun, M. L., Tsunekawa, A., Haregeweyn, N., Meshesha, D. T., Adgo, E., Tsubo, M., Masunaga, T., Fenta, A. A., Sultan, D., & Yibeltal, M. (2019b). Exploring land use/land cover changes, drivers and their implications in contrasting agro-ecological environments of Ethiopia. *Land Use Policy*, 87(March). <https://doi.org/10.1016/j.landusepol.2019.104052>
- Beroho, M., Briak, H., Cherif, E. K., Boulahfa, I., Ouallali, A., Mrabet, R., Kebede, F., Bernardino, A., & Aboumaria, K. (2023). Future Scenarios of Land Use/Land Cover (LULC) Based on a CA-Markov Simulation Model: Case of a Mediterranean Watershed in Morocco. *Remote Sensing*, 15(4). <https://doi.org/10.3390/rs15041162>
- Bewket, W., & Conway, D. (2007). A note on the temporal and spatial variability of rainfall in the drought-prone Amhara region of Ethiopia. *International Journal of Climatology: A Journal of the Royal Meteorological Society*, 27(11), 1467–1477.
- Beyene, A., & Shumetie, A. (2023). Green Legacy Initiative for Sustainable Economic Development in Ethiopia. In *Augmenting Economic Governance in Ethiopia (AEGE)* (Issue February).
- Beyer, R., Krapp, M., & Manica, A. (2019). A systematic comparison of bias correction methods for paleoclimate simulations. *A Systematic Comparison of Bias Correction Methods for Paleoclimate Simulations*, February, 1–23. <https://doi.org/10.5194/cp-2019-11>
- Bhattacharjee, P. S., & Zaitchik, B. F. (2015). Perspectives on CMIP5 model performance in the Nile River headwaters regions. *International Journal of Climatology*, 35(14), 4262–4275. <https://doi.org/10.1002/joc.4284>
- Bibi, T. S. (2023). Derivation of short-term design rainfall intensity from daily rainfall data for urban drainage design using empirical equations in robe town, Ethiopia. *International Journal of Hydrology*, 7(2), 63–71. <https://doi.org/10.15406/ijh.2023.07.00340>
- Bogale, A. (2020). Review, impact of land use/cover change on soil erosion in the Lake Tana Basin, Upper Blue Nile, Ethiopia. *Applied Water Science*, 10(12), 1–6. <https://doi.org/10.1007/s13201-020-01325-w>
- Braimah, A. K. (2006). Random and systematic land-cover transitions in northern Ghana. *Agriculture, Ecosystems and Environment*, 113(1–4), 254–263. <https://doi.org/10.1016/j.agee.2005.10.019>
- Breiman, L. (2001). Random forests. *Machine Learning*, 45, 5–32.
- Breiman, L. (2018). Breiman and Cutler’s random forests for classification and regression. *R Package Version*, 3(3).
- Brunner, G. W. (2014). Combined 1D and 2D Modeling with HEC-RAS. *Usace, Outubro*, 1–130.
- Brunner, G. W. (2024a). HEC-RAS HEC-RAS 2D User ’ s Manual. *U.S. Army Corps of Engineers*, 6.5(May), 1–272.
- Brunner, G. W. (2024b). HEC-RAS HEC-RAS Hydraulic Reference. *U.S. Army Corps of Engineers*, 6.5(May), 1–477. <https://www.hec.usace.army.mil/confluence/rasdocs/ras1dtechref/latest/introduction>
- Bulti, D. T., Abebe, B. G., & Biru, Z. (2021). Analysis of the changes in historical and future extreme precipitation under climate change in Adama city, Ethiopia. *Modeling Earth Systems and Environment*, 7(4), 2575–2587.

<https://doi.org/10.1007/s40808-020-01019-x>

- Camargo, F. F., Sano, E. E., Almeida, C. M., Mura, J. C., & Almeida, T. (2019). A comparative assessment of machine-learning techniques for land use and land cover classification of the Brazilian tropical savanna using ALOS-2/PALSAR-2 polarimetric images. *Remote Sensing*, 11(13). <https://doi.org/10.3390/rs11131600>
- Casulli, V. (2009). A high-resolution wetting and drying algorithm for free-surface hydrodynamics. *International Journal for Numerical Methods in Fluids*, 60(4), 391–408.
- Cauteruccio, A., Brambilla, E., Stagnaro, M., Lanza, L. G., & Rocchi, D. (2021). Experimental evidence of the wind-induced bias of precipitation gauges using particle image velocimetry and particle tracking in the wind tunnel. *Journal of Hydrology*, 600, 126690.
- Chakilu, G. G., & Moges, M. A. (2017). Assessing the Land Use/Cover Dynamics and its Impact on the Low Flow of Gumara Watershed, Upper Blue Nile Basin, Ethiopia. *Hydrology: Current Research*, 08(01), 1–6. <https://doi.org/10.4172/2157-7587.1000268>
- Chakilu, G. G., Sándor, S., & Zoltán, T. (2020). Change in stream flow of gumara watershed, upper blue nile basin, ethiopia under representative concentration pathway climate change scenarios. *Water (Switzerland)*, 12(11), 1–14. <https://doi.org/10.3390/w12113046>
- Chakilu, G. G., Sándor, S., & Zoltán, T. (2023). The Dynamics of Hydrological Extremes under the Highest Emission Climate Change Scenario in the Headwater Catchments of the Upper Blue Nile Basin, Ethiopia. *Water (Switzerland)*, 15(2). <https://doi.org/10.3390/w15020358>
- Chang, X., Zhang, F., Cong, K., & Liu, X. (2021). Scenario simulation of land use and land cover change in mining area. *Scientific Reports*, 11(1), 1–12. <https://doi.org/10.1038/s41598-021-92299-5>
- Chaudhry, M. H. (2008). *Open-channel flow* (Vol. 523). Springer.
- Chen, C. A., Hsu, H. H., & Liang, H. C. (2021). Evaluation and comparison of CMIP6 and CMIP5 model performance in simulating the seasonal extreme precipitation in the Western North Pacific and East Asia. *Weather and Climate Extremes*, 31, 100303. <https://doi.org/10.1016/j.wace.2021.100303>
- Chen, Q., Chen, H., Zhang, J., Hou, Y., Shen, M., Chen, J., & Xu, C. (2020). Impacts of climate change and LULC change on runoff in the Jinsha River Basin. *Journal of Geographical Sciences*, 30(1), 85–102. <https://doi.org/10.1007/s11442-020-1716-9>
- Chen, Y., Xu, Y., & Yin, Y. (2009). Impacts of land use change scenarios on storm-runoff generation in Xitiao basin, China. *Quaternary International*, 208(1–2), 121–128.
- Cherie, N. Z. (2013). *Downscaling and modeling the effects of climate change on hydrology and water resources in the Upper Blue Nile River Basin, Ethiopia*. Universitätsbibliothek Kassel.
- Chinasho, A., Bedadi, B., Lemma, T., Tana, T., Hordofa, T., & Elias, B. (2021). Evaluation of Seven Gap-Filling Techniques for Daily Station-Based Rainfall Datasets in South Ethiopia. *Advances in Meteorology*, 2021. <https://doi.org/10.1155/2021/9657460>
- Chow, V. T., Maidment, D. R., & Mays, L. W. (1988). *Applied hydrology*.
- Clement, M. A., Kilsby, C. G., & Moore, P. (2018a). Multi-temporal synthetic aperture radar flood mapping using change detection. *J. Flood Risk Manag.* 11, 152–168.
- Clement, M. A., Kilsby, C. G., & Moore, P. (2018b). Multi-temporal synthetic aperture radar flood mapping using change detection. *Journal of Flood Risk Management*, 11(2), 152–168. <https://doi.org/10.1111/jfr3.12303>
- Cochrane, L., & Hadis, S. (2019). Functionality of the land certification program in Ethiopia: Exploratory evaluation of the processes of updating certificates. *Land*, 8(10), 149.
- Cohen, J. (2013). *Statistical power analysis for the behavioral sciences*. Academic press.
- Congalton, R. G. (2001). Accuracy assessment and validation of remotely sensed and other spatial information. *International Journal of Wildland Fire*, 10(3–4), 321–328. <https://doi.org/10.1071/wf01031>
- Congalton, R. G., & Green, K. (2019). *Assessing the accuracy of remotely sensed data: principles and practices*. CRC press.
- Conway, D. (2000). The climate and hydrology of the Upper Blue Nile River. *Geographical Journal*, 166(1), 49–62.
- Costabile, P., Costanzo, C., Ferraro, D., Macchione, F., & Petaccia, G. (2020). Performances of the new HEC-RAS version 5 for 2-D hydrodynamic-based rainfall-runoff simulations at basin scale: Comparison with a state-of-the art model. *Water (Switzerland)*, 12(9), 1–19. <https://doi.org/10.3390/W12092326>
- Cramér, H. (1999). *Mathematical methods of statistics* (Vol. 43). Princeton university press.
- Cronshey, R. (1986). *Urban hydrology for small watersheds* (Issue 55). US Department of Agriculture, Soil Conservation Service, Engineering Division.
- Cunge, J. A. (1969). On the subject of a flood propagation computation method (Muskingum method). *Journal of Hydraulic Research*, 7(2), 205–230.
- Cuo, L. (2016). Land Use/Cover Change Impacts on Hydrology in Large River Basins: A Review. In *Terrestrial Water Cycle and Climate Change: Natural and Human-Induced Impacts* (pp. 103–134). wiley. <https://doi.org/10.1002/9781118971772.ch6>
- Cuyppers, S., Nascetti, A., & Vergauwen, M. (2023). Land Use and Land Cover Mapping with VHR and Multi-Temporal Sentinel-2 Imagery. *Remote Sensing*, 15(10), 2501.

- Darling, D. A. (1957). The kolmogorov-smirnov, cramer-von mises tests. *The Annals of Mathematical Statistics*, 28(4), 823–838.
- Dawit, M., Halefom, A., Teshome, A., Sisay, E., Shewayirga, B., & Dananto, M. (2019). Changes and variability of precipitation and temperature in the Guna Tana watershed, Upper Blue Nile Basin, Ethiopia. *Modeling Earth Systems and Environment*, 5(4), 1395–1404. <https://doi.org/10.1007/s40808-019-00598-8>
- DEFRA, E. A. (2005). *Flood Risk Assessment Guidance for New Development*. Phase.
- Déqué, M. (2007). Frequency of precipitation and temperature extremes over France in an anthropogenic scenario: Model results and statistical correction according to observed values. *Global and Planetary Change*, 57(1–2), 16–26. <https://doi.org/10.1016/j.gloplacha.2006.11.030>
- Desta, M. A., Zeleke, G., Payne, W. A., Shenkoru, T., & Dile, Y. (2019). The impacts of rice cultivation on an indigenous Fogera cattle population at the eastern shore of Lake Tana, Ethiopia. *Ecological Processes*, 8(1). <https://doi.org/10.1186/s13717-019-0167-7>
- Dibaba, W. T., Demissie, T. A., & Miegel, K. (2020). Drivers and implications of land use/land cover dynamics in Finchaa catchment, northwestern Ethiopia. *Land*, 9(4), 113.
- Dibaba, W. T., Miegel, K., & Demissie, T. A. (2019). Evaluation of the CORDEX regional climate models performance in simulating climate conditions of two catchments in Upper Blue Nile Basin. *Dynamics of Atmospheres and Oceans*, 87(August), 101104. <https://doi.org/10.1016/j.dynatmoce.2019.101104>
- Dimitriadis, P., Tegos, A., Oikonomou, A., Pagana, V., Koukouvinos, A., Mamassis, N., Koutsoyiannis, D., & Efstratiadis, A. (2016). Comparative evaluation of 1D and quasi-2D hydraulic models based on benchmark and real-world applications for uncertainty assessment in flood mapping. *Journal of Hydrology*, 534, 478–492. <https://doi.org/10.1016/j.jhydrol.2016.01.020>
- Du, H., Xia, J., Yan, Y., Lu, Y., & Li, J. (2022). Spatiotemporal Variations of Extreme Precipitation in Wuling Mountain Area (China) and Their Connection to Potential Driving Factors. *Sustainability (Switzerland)*, 14(14). <https://doi.org/10.3390/su14148312>
- Dutta, D., Herath, S., & Musiake, K. (2003). A mathematical model for flood loss estimation. *Journal of Hydrology*, 277(1–2), 24–49. [https://doi.org/10.1016/S0022-1694\(03\)00084-2](https://doi.org/10.1016/S0022-1694(03)00084-2)
- Eastman, J. (2009). *IDRISI Taiga: Guide to GIS and Image Processing Volume - Manual version 16.02. August*, 325.
- Eccles, R., Zhang, H., & Hamilton, D. (2019). A review of the effects of climate change on riverine flooding in subtropical and tropical regions. *Journal of Water and Climate Change*, 10(4), 687–707. <https://doi.org/10.2166/wcc.2019.175>
- Elkhrachy, I. (2015). Flash Flood Hazard Mapping Using Satellite Images and GIS Tools: A case study of Najran City, Kingdom of Saudi Arabia (KSA). *Egyptian Journal of Remote Sensing and Space Science*, 18(2), 261–278. <https://doi.org/10.1016/j.ejrs.2015.06.007>
- Elkhrachy, I., Pham, Q. B., Costache, R., Mohajane, M., Rahman, K. U., Shahabi, H., Linh, N. T. T., & Anh, D. T. (2021). Sentinel-1 remote sensing data and Hydrologic Engineering Centres River Analysis System two-dimensional integration for flash flood detection and modelling in New Cairo City, Egypt. *Journal of Flood Risk Management*, 14(2), 1–17. <https://doi.org/10.1111/jfr3.12692>
- Elshamy, M. E., Seierstad, I. A., & Sorteberg, A. (2009). Impacts of climate change on Blue Nile flows using bias-corrected GCM scenarios. *Hydrology and Earth System Sciences*, 13(5), 551–565.
- Emam, A. R., Mishra, B. K., Kumar, P., Masago, Y., & Fukushi, K. (2016). Impact assessment of climate and land-use changes on flooding behavior in the upper ciliwung river, jakarta, Indonesia. *Water (Switzerland)*, 8(12). <https://doi.org/10.3390/w8120559>
- Enayati, M., Bozorg-Haddad, O., Bazrafshan, J., Hejabi, S., & Chu, X. (2021). Bias correction capabilities of quantile mapping methods for rainfall and temperature variables. *Journal of Water and Climate Change*, 12(2), 401–419. <https://doi.org/10.2166/wcc.2020.261>
- Endalew, G. J. (2007). *Changes in the frequency and intensity of extremes over Northeast Africa* (Issue 26). Citeseer.
- Eyring, V., Bony, S., Meehl, G. A., Senior, C. A., Stevens, B., Stouffer, R. J., & Taylor, K. E. (2016). Overview of the Coupled Model Intercomparison Project Phase 6 (CMIP6) experimental design and organization. *Geoscientific Model Development*, 9(5), 1937–1958. <https://doi.org/10.5194/gmd-9-1937-2016>
- Ezzine, A., Saidi, S., Hermassi, T., Kammessi, I., Darragi, F., & Rajhi, H. (2020). Flood mapping using hydraulic modeling and Sentinel-1 image: Case study of Medjerda Basin, northern Tunisia. *Egyptian Journal of Remote Sensing and Space Science*, 23(3), 303–310. <https://doi.org/10.1016/j.ejrs.2020.03.001>
- Faichia, C., Tong, Z., Zhang, J., Liu, X., Kazuva, E., Ullah, K., & Al-Shaibah, B. (2020). Using rs data-based ca-markov model for dynamic simulation of historical and future lucc in Vientiane, Laos. *Sustainability*, 12(20), 1–20. <https://doi.org/10.3390/su12208410>
- Famien, A. M., Janicot, S., Delfin Ochou, A., Vrac, M., Defrance, D., Sultan, B., & Noël, T. (2018). A bias-corrected CMIP5 dataset for Africa using the CDF-t method - A contribution to agricultural impact studies. *Earth System Dynamics*, 9(1), 313–338. <https://doi.org/10.5194/esd-9-313-2018>
- Fan, Z., Li, W., Jiang, Q., Sun, W., Wen, J., & Gao, J. (2021). A Comparative Study of Four Merging Approaches for Regional Precipitation Estimation. *IEEE Access*, 9, 33625–33637. <https://doi.org/10.1109/ACCESS.2021.3057057>

- Farooq, M., Shafique, M., & Shahzad, M. (2019). Flood hazard assessment and mapping of River Swat using HEC - RAS 2D model and high - resolution 12 - m TanDEM - X DEM. *Natural Hazards*, 0123456789. <https://doi.org/10.1007/s11069-019-03638-9>
- Farr, T. G., Rosen, P. A., Caro, E., Crippen, R., Duren, R., Hensley, S., Kobrick, M., Paller, M., Rodriguez, E., & Roth, L. (2007). The shuttle radar topography mission. *Reviews of Geophysics*, 45(2).
- Fekadu, A. (2018). Detecting flash flood hazard areas using geo-spatial-based analytic hierarchy process in Weidie watershed South Western Ethiopia. *Journal of Remote Sensing & GIS*, 7(02), 1–5.
- FEMA, F. E. M. A. (2003). *Guidelines and specifications for flood hazard mapping partners*. Federal Emergency Management Agency Washington, DC, USA.
- Fikreyesus, D., Gizaw, S., Mayers, J., & Barrett, S. (2022). *Mass tree planting: prospects for a green legacy in Ethiopia*.
- Filipponi, F. (2019). Sentinel-1 GRD preprocessing workflow. *Proceedings*, 18(1), 11.
- Fiorillo, E., & Tarchiani, V. (2017). A simplified hydrological method for flood risk assessment at sub-basin level in Niger. *Green Energy and Technology*, 0(9783319590950), 247–263. https://doi.org/10.1007/978-3-319-59096-7_12
- Fischer, T., Su, B., Luo, Y., & Scholten, T. (2012). Probability distribution of precipitation extremes for weather index-based insurance in the Zhujiang River Basin, South China. *Journal of Hydrometeorology*, 13(3), 1023–1037. <https://doi.org/10.1175/JHM-D-11-041.1>
- Fofana, M., Adoukpe, J., Larbi, I., Hounkpe, J., Djan'na Koubodana, H., Toure, A., Bokar, H., Dotse, S. Q., & Limantol, A. M. (2022). Urban flash flood and extreme rainfall events trend analysis in Bamako, Mali. *Environmental Challenges*, 6(August 2021), 100449. <https://doi.org/10.1016/j.envc.2022.100449>
- Foody, G. M. (2002). Status of land cover classification accuracy assessment. *Remote Sensing of Environment*, 80(1), 185–201.
- Funk, C., Peterson, P., Landsfeld, M., Pedreros, D., Verdin, J., Shukla, S., Husak, G., Rowland, J., Harrison, L., Hoell, A., & Michaelsen, J. (2015). The climate hazards infrared precipitation with stations - A new environmental record for monitoring extremes. *Scientific Data*, 2, 1–21. <https://doi.org/10.1038/sdata.2015.66>
- Gashaw, T., Tulu, T., Argaw, M., & Worqlul, A. W. (2018). Modeling the hydrological impacts of land use/land cover changes in the Andassa watershed, Blue Nile Basin, Ethiopia. *Science of the Total Environment*, 619–620, 1394–1408. <https://doi.org/10.1016/j.scitotenv.2017.11.191>
- Gashaw, T., Worqlul, A. W., Lakew, H., Taye, M. T., Seid, A., & Hailelassie, A. (2023). Evaluations of satellite/reanalysis rainfall and temperature products in the Bale Eco-Region (Southern Ethiopia) to enhance the quality of input data for hydro-climate studies. *Remote Sensing Applications: Society and Environment*, 31, 100994.
- Gashaw, W., & Legesse, D. (2011). Flood Hazard and Risk Assessment Using GIS and Remote Sensing in Fogera Woreda, Northwest Ethiopia. *Nile River Basin*, 6(9), 179–206. https://doi.org/10.1007/978-94-007-0689-7_9
- Gebrechorkos, S. H., Hülsmann, S., & Bernhofer, C. (2019). Long-term trends in rainfall and temperature using high-resolution climate datasets in East Africa. *Scientific Reports*, 9(1), 1–9. <https://doi.org/10.1038/s41598-019-47933-8>
- Gebrechorkos, S., Leyland, J., Slater, L., Wortmann, M., Ashworth, P. J., Bennett, G. L., Boothroyd, R., Cloke, H., Delorme, P., Griffith, H., Hardy, R., Hawker, L., McLelland, S., Neal, J., Nicholas, A., Tatem, A. J., Vahidi, E., Parsons, D. R., & Darby, S. E. (2023). A high-resolution daily global dataset of statistically downscaled CMIP6 models for climate impact analyses. *Scientific Data*, 10(1), 1–15. <https://doi.org/10.1038/s41597-023-02528-x>
- Gebresellase, S. H., Wu, Z., Xu, H., & Muhammad, W. I. (2023). Scenario-Based LULC Dynamics Projection Using the CA-Markov Model on Upper Awash Basin (UAB), Ethiopia. *Sustainability*, 15(2), 1683. <https://doi.org/10.3390/su15021683>
- Getachew, B., & Manjunatha, B. R. (2022). Impacts of Land-Use Change on the Hydrology of Lake Tana Basin, Upper Blue Nile River Basin, Ethiopia. *Global Challenges*, 2200041, 1–13. <https://doi.org/10.1002/gch2.202200041>
- Getachew, B., Manjunatha, B. R., & Bhat, H. G. (2021). Modeling projected impacts of climate and land use/land cover changes on hydrological responses in the Lake Tana Basin, upper Blue Nile River Basin, Ethiopia. *Journal of Hydrology*, 595(January), 125974. <https://doi.org/10.1016/j.jhydrol.2021.125974>
- Getahun, Y. S., & Gebre, S. L. (2015). Flood hazard assessment and mapping of flood inundation area of the Awash River Basin in Ethiopia using GIS and HEC-GeoRAS/HEC-RAS model. *Journal of Civil & Environmental Engineering*, 5(4), 1.
- Ghimire, E., Sharma, S., & Lamichhane, N. (2020). Evaluation of one-dimensional and two-dimensional HEC-RAS models to predict flood travel time and inundation area for flood warning system ABSTRACT. *ISH Journal of Hydraulic Engineering*, 00(00), 1–17. <https://doi.org/10.1080/09715010.2020.1824621>
- Ghonchepour, D., Sadoddin, A., Bahremand, A., Croke, B., Jakeman, A., & Salmanmahiny, A. (2021). A methodological framework for the hydrological model selection process in water resource management projects. *Natural Resource Modeling*, 34(3). <https://doi.org/10.1111/nrm.12326>
- Ghorbanian, A., Mohammadzadeh, A., Jamali, S., & Duan, Z. (2022). Performance Evaluation of Six Gridded Precipitation Products throughout Iran Using Ground Observations over the Last Two Decades (2000–2020).

- Remote Sensing*, 14(15). <https://doi.org/10.3390/rs14153783>
- Githungo, W., Otengi, S., Wakhungu, J., & Masibayi, E. (2016). Infilling monthly rain gauge data gaps with satellite estimates for ASAL of Kenya. *Hydrology*, 3(4). <https://doi.org/10.3390/hydrology3040040>
- Giustarini, L., Hostache, R., Matgen, P., Schumann, G. J.-P., Bates, P. D., & Mason, D. C. (2012). A change detection approach to flood mapping in urban areas using TerraSAR-X. *IEEE Transactions on Geoscience and Remote Sensing*, 51(4), 2417–2430.
- Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., & Moore, R. (2017). Google Earth Engine: Planetary-scale geospatial analysis for everyone. *Remote Sensing of Environment*, 202, 18–27.
- Goshu, G., Koelmans, A. A., & de Klein, J. J. M. (2017). Water quality of Lake Tana basin, Upper Blue Nile, Ethiopia. A review of available data. *Social and Ecological System Dynamics: Characteristics, Trends, and Integration in the Lake Tana Basin, Ethiopia*, 127–141.
- Grimaldi, S., Xu, J., Li, Y., Pauwels, V. R. N., & Walker, J. P. (2020). Flood mapping under vegetation using single SAR acquisitions. *Remote Sensing of Environment*, 237, 111582.
- Guerhazi, E., Milano, M., & Reynard, E. (2019). Performance evaluation of satellite-based rainfall products on hydrological modeling for a transboundary catchment in northwest Africa. *Theoretical and Applied Climatology*, 138(3–4), 1695–1713. <https://doi.org/10.1007/s00704-019-02928-3>
- Gummadi, S., Rao, K. P. C., Seid, J., Legesse, G., Kadiyala, M. D. M., Takele, R., Amede, T., & Whitbread, A. (2018). Spatio-temporal variability and trends of precipitation and extreme rainfall events in Ethiopia in 1980–2010. *Theoretical and Applied Climatology*, 134, 1315–1328.
- Gupta, H. V., Sorooshian, S., & Yapo, P. O. (1999). Status of automatic calibration for hydrologic models: Comparison with multilevel expert calibration. *Journal of Hydrologic Engineering*, 4(2), 135–143.
- Haile, A. T., Akawka, A. L., Berhanu, B., & Rientjes, T. (2017). Changes in water availability in the Upper Blue Nile basin under the representative concentration pathways scenario. *Hydrological Sciences Journal*, 62(13), 2139–2149.
- Haile, A. T., Rientjes, T., Gieske, A., & Gebremichael, M. (2009). Rainfall variability over mountainous and adjacent lake areas: The case of Lake Tana basin at the source of the Blue Nile River. *Journal of Applied Meteorology and Climatology*, 48(8), 1696–1717. <https://doi.org/10.1175/2009JAMC2092.1>
- Halmy, M. W. A., Gessler, P. E., Hicke, J. A., & Salem, B. B. (2015). Land use/land cover change detection and prediction in the north-western coastal desert of Egypt using Markov-CA. *Applied Geography*, 63, 101–112. <https://doi.org/10.1016/j.apgeog.2015.06.015>
- Hamad, R., Balzter, H., & Kolo, K. (2018). Predicting land use/land cover changes using a CA-Markov model under two different scenarios. *Sustainability (Switzerland)*, 10(10), 1–23. <https://doi.org/10.3390/su10103421>
- Hamed, M. M., Nashwan, M. S., Shiru, M. S., & Shahid, S. (2022). Comparison between CMIP5 and CMIP6 Models over MENA Region Using Historical Simulations and Future Projections. *Sustainability (Switzerland)*, 14(16). <https://doi.org/10.3390/su141610375>
- Hare, W. (2003). Assessment of Knowledge on Impacts of Climate Change – Contribution to the Specification of Art. 2 of the UNFCCC. In *Wissenschaftliche Beirat der Bundesregierung Globale Umweltveränderungen* (Issue 1). http://www.wbgu.de/wbgu_sn2003_ex01.pdf
- Heimhuber, V., Hannemann, J. C., & Rieger, W. (2015). Flood risk management in remote and impoverished areas—a case study of Onaville, Haiti. *Water (Switzerland)*, 7(7), 3832–3860. <https://doi.org/10.3390/w7073832>
- Hirsch, C. (1990). Numerical computation of internal and external flows. *Computational Methods for Inviscid and Viscous Flows*, 2.
- Hirsch, R. M. (1982). A comparison of four streamflow record extension techniques. *Water Resources Research*, 18(4), 1081–1088. <https://doi.org/10.1029/WR018i004p01081>
- Hosking, J. R. M., & Wallis, J. R. (1997). *Regional frequency analysis*.
- Hounguè, N. R., Almoradie, A. D. S., & Evers, M. (2022). A Multi Criteria Decision Analysis Approach for Regional Climate Model Selection and Future Climate Assessment in the Mono River Basin, Benin and Togo. *Atmosphere*, 13(9). <https://doi.org/10.3390/atmos13091471>
- Huang, M., & Jin, S. (2020). Rapid flood mapping and evaluation with a supervised classifier and change detection in Shouguang using Sentinel-1 SAR and Sentinel-2 optical data. *Remote Sensing*, 12(13), 2073.
- Huete, A. R. (1988). A soil-adjusted vegetation index (SAVI). *Remote Sensing of Environment*, 25(3), 295–309.
- Hwang, C.-L., & Yoon, K. (1981). Methods for multiple attribute decision making. In *Multiple attribute decision making* (pp. 58–191). Springer.
- IPCC. (2013). *Climate change 2013: the physical science basis. Contribution of Working Group I to the fifth assessment report of the Intergovernmental Panel on Climate Change*.
- IPCC. (2021). *Assessment Report 6 Climate Change 2021: The Physical Science Basis*.
- Iqbal, Z., Shahid, S., Ahmed, K., Wang, X., Ismail, T., & Gabriel, H. F. (2022). Bias correction method of high-resolution satellite-based precipitation product for Peninsular Malaysia. *Theoretical and Applied Climatology*, 148(3–4), 1429–1446. <https://doi.org/10.1007/s00704-022-04007-6>
- Irannezhad, M., Minaei, M., Ahmadian, S., & Chen, D. (2018). Impacts of changes in climate and land cover-land use on

- flood characteristics in Gorganrood Watershed (Northeastern Iran) during recent decades*. *Geografiska Annaler, Series A: Physical Geography*, 100(4), 340–350. <https://doi.org/10.1080/04353676.2018.1515578>
- Jemberie, M. A., Awass, A. A., Melesse, A. M., Ayele, G. T., & Demissie, S. S. (2016). Seasonal rainfall–runoff variability analysis, Lake Tana Sub-Basin, Upper Blue Nile Basin, Ethiopia. *Landscape Dynamics, Soils and Hydrological Processes in Varied Climates*, 341–363.
- Jiang, Z., Li, W., Xu, J., & Li, L. (2015). Extreme precipitation indices over China in CMIP5 models. Part I: Model evaluation. *Journal of Climate*, 28(21), 8603–8619. <https://doi.org/10.1175/JCLI-D-15-0099.1>
- Johary, R., Révillion, C., Catry, T., Alexandre, C., Mouquet, P., Rakotoniaina, S., Pennober, G., & Rakotondraompiana, S. (2023). Detection of Large-Scale Floods Using Google Earth Engine and Google Colab. *Remote Sensing*, 15(22). <https://doi.org/10.3390/rs15225368>
- Jose, D. M., & Dwarakish, G. S. (2022). Ranking of downscaled CMIP5 and CMIP6 GCMs at a basin scale: case study of a tropical river basin on the South West coast of India. *Arabian Journal of Geosciences*, 15(1), 1–23. <https://doi.org/10.1007/s12517-021-09289-0>
- Jose, D. M., Vincent, A. M., & Dwarakish, G. S. (2022). Improving multiple model ensemble predictions of daily precipitation and temperature through machine learning techniques. *Scientific Reports*, 12(1), 1–25. <https://doi.org/10.1038/s41598-022-08786-w>
- Kadri, N., Jebari, S., Augusseau, X., Mahdhi, N., Lestrelin, G., & Berndtsson, R. (2023). Analysis of Four Decades of Land Use and Land Cover Change in Semiarid Tunisia Using Google Earth Engine. *Remote Sensing*, 15(13). <https://doi.org/10.3390/rs15133257>
- Kafy, A. A., Naim, M. N. H., Subramanyam, G., Faisal, A. Al, Ahmed, N. U., Rakib, A. Al, Kona, M. A., & Sattar, G. S. (2021). Cellular Automata approach in dynamic modelling of land cover changes using RapidEye images in Dhaka, Bangladesh. *Environmental Challenges*, 4(March), 100084. <https://doi.org/10.1016/j.envc.2021.100084>
- Kamaraj, M., & Rangarajan, S. (2022). Predicting the future land use and land cover changes for Bhavani basin, Tamil Nadu, India, using QGIS MOLUSCE plugin. *Environmental Science and Pollution Research*, 29(57), 86337–86348. <https://doi.org/10.1007/s11356-021-17904-6>
- Kamruzzaman, M., Shahid, S., Islam, A. T., Hwang, S., Cho, J., Zaman, M. A. U., Ahmed, M., Rahman, M. M., & Hossain, M. B. (2021). Comparison of CMIP6 and CMIP5 model performance in simulating historical precipitation and temperature in Bangladesh: a preliminary study. *Theoretical and Applied Climatology*, 145(3–4), 1385–1406. <https://doi.org/10.1007/s00704-021-03691-0>
- Kassa, H., Abiyu, A., Hagazi, N., Mokria, M., Kassawmar, T., & Gitz, V. (2022). Forest landscape restoration in Ethiopia: Progress and challenges. *Frontiers in Forests and Global Change*, 5. <https://doi.org/10.3389/ffgc.2022.796106>
- Kassaye, S. M., Tadesse, T., Tegegne, G., & Hordofa, A. T. (2024). Quantifying the climate change impacts on the magnitude and timing of hydrological extremes in the Baro River Basin, Ethiopia. *Environmental Systems Research*, 13(1), 1–15. <https://doi.org/10.1186/s40068-023-00328-1>
- Kaur, K., & Kaur, N. (2023). Comparison of bias correction methods for climate change projections in the lower Shivaliks of Punjab. *Journal of Water and Climate Change*, 14(8), 2606–2625. <https://doi.org/10.2166/wcc.2023.503>
- Khoi, D. N., Quan, N. T., Nhi, P. T. T., & Nguyen, V. T. (2021). Impact of climate change on precipitation extremes over Ho Chi Minh city, Vietnam. *Water (Switzerland)*, 13(2). <https://doi.org/10.3390/w13020120>
- Kim, J. B., Habimana, J. de D., Kim, S. H., & Bae, D. H. (2021). Assessment of climate change impacts on the hydroclimatic response in burundi based on cmip6 esms. *Sustainability (Switzerland)*, 13(21), 1–21. <https://doi.org/10.3390/su132112037>
- Kim, U., & Kaluarachchi, J. J. (2009). Climate change impacts on water resources in the upper blue Nile River Basin, Ethiopia 1. *JAWRA Journal of the American Water Resources Association*, 45(6), 1361–1378.
- Kim, Y.-H., Min, S.-K., Zhang, X., Sillmann, J., & Sandstad, M. (2020). Evaluation of the CMIP6 multi-model ensemble for climate extreme indices. *Weather and Climate Extremes*, 29, 100269.
- Kirpich, Z. P. (1940). Time of concentration of small agricultural watersheds. *Civil Engineering*, 10(6), 362.
- Kumar, H., Karwariya, S. K., & Kumar, R. (2022). Google Earth Engine-Based Identification of Flood Extent and Flood-Affected Paddy Rice Fields Using Sentinel-2 MSI and Sentinel-1 SAR Data in Bihar State, India. *Journal of the Indian Society of Remote Sensing*, 50(5), 791–803. <https://doi.org/10.1007/s12524-021-01487-3>
- Kundu, P. M., & Olang, L. O. (2011). The impact of land use change on runoff and peak flood discharges for the Nyando River in Lake Victoria drainage basin, Kenya. *WIT Transactions on Ecology and the Environment*, 153, 83–94. <https://doi.org/10.2495/WS110081>
- Lakew, H. B., Moges, S. A., & Asfaw, D. H. (2020). Hydrological performance evaluation of multiple satellite precipitation products in the upper Blue Nile basin, Ethiopia. *Journal of Hydrology: Regional Studies*, 27(August 2018), 100664. <https://doi.org/10.1016/j.ejrh.2020.100664>
- Landis, J. R., & Koch, G. G. (1977). The measurement of observer agreement for categorical data. *Biometrics*, 159–174.
- Lane, R. A., & Kay, A. L. (2021). Climate Change Impact on the Magnitude and Timing of Hydrological Extremes Across Great Britain. *Frontiers in Water*, 3(July), 1–14. <https://doi.org/10.3389/frwa.2021.684982>

- Lee, J.-S., Jurkevich, L., Dewaele, P., Wambacq, P., & Oosterlinck, A. (1994). Speckle filtering of synthetic aperture radar images: A review. *Remote Sensing Reviews*, 8(4), 313–340.
- Legates, D. R., & McCabe Jr, G. J. (1999). Evaluating the use of “goodness-of-fit” measures in hydrologic and hydroclimatic model validation. *Water Resources Research*, 35(1), 233–241.
- Lenderink, G., Buishand, A., & Van Deursen, W. (2007). Estimates of future discharges of the river Rhine using two scenario methodologies: Direct versus delta approach. *Hydrology and Earth System Sciences*, 11(3), 1145–1159. <https://doi.org/10.5194/hess-11-1145-2007>
- Leta, M. K., Demissie, T. A., & Tränckner, J. (2021a). Modeling and prediction of land use land cover change dynamics based on land change modeler (Lcm) in nashe watershed, upper blue nile basin, Ethiopia. *Sustainability*, 13(7). <https://doi.org/10.3390/su13073740>
- Leta, M. K., Demissie, T. A., & Tränckner, J. (2021b). Modeling and prediction of land use land cover change dynamics based on land change modeler (Lcm) in nashe watershed, upper blue nile basin, Ethiopia. *Sustainability (Switzerland)*, 13(7). <https://doi.org/10.3390/su13073740>
- Li, Y., Martinis, S., Plank, S., & Ludwig, R. (2018). An automatic change detection approach for rapid flood mapping in Sentinel-1 SAR data. *International Journal of Applied Earth Observation and Geoinformation*, 73, 123–135.
- Liemohn, M. W., Shane, A. D., Azari, A. R., Petersen, A. K., Swiger, B. M., & Mukhopadhyay, A. (2021). RMSE is not enough: Guidelines to robust data-model comparisons for magnetospheric physics. *Journal of Atmospheric and Solar-Terrestrial Physics*, 218(December 2020), 105624. <https://doi.org/10.1016/j.jastp.2021.105624>
- Likinaw, A., Alemayehu, A., & Bewket, W. (2023). Trends in Extreme Precipitation Indices in Northwest Ethiopia: Comparative Analysis Using the Mann–Kendall and Innovative Trend Analysis Methods. *Climate*, 11(8), 164.
- LIN, W., & CHEN, H. (2020). Assessment of model performance of precipitation extremes over the mid-high latitude areas of Northern Hemisphere: from CMIP5 to CMIP6. *Atmospheric and Oceanic Science Letters*, 13(6), 598–603. <https://doi.org/10.1080/16742834.2020.1820303>
- Liping, C., Yujun, S., & Saeed, S. (2018). Monitoring and predicting land use and land cover changes using remote sensing and GIS techniques—A case study of a hilly area, Jiangle, China. *PLoS ONE*, 13(7), 1–23. <https://doi.org/10.1371/journal.pone.0200493>
- Londhe, D. S., Katpatal, Y. B., & Bokde, N. D. (2023). Performance Assessment of Bias Correction Methods for Precipitation and Temperature from CMIP5 Model Simulation. *Applied Sciences (Switzerland)*, 13(16). <https://doi.org/10.3390/app13169142>
- Long, S., Fatoyinbo, T. E., & Policelli, F. (2014a). Flood extent mapping for Namibia using change detection and thresholding with SAR. *Environmental Research Letters*, 9(3), 35002.
- Long, S., Fatoyinbo, T. E., & Policelli, F. (2014b). Flood extent mapping for Namibia using change detection and thresholding with SAR. *Environmental Research Letters*, 9(3). <https://doi.org/10.1088/1748-9326/9/3/035002>
- Loukili, Y., Lakhressi, Y., & Ali, S. E. Ben. (2025). Flood Mapping Methodologies in Google Earth Engine Using Optical and Radar Data: A Comparative Study. *Journal of Environmental and Earth Sciences*, 7(1), 363–380. <https://doi.org/10.30564/jees.v7i1.7397>
- Lukas, P., Melesse, A. M., & Kenea, T. T. (2023). Prediction of Future Land Use/Land Cover Changes Using a Coupled CA-ANN Model in the Upper Omo–Gibe River Basin, Ethiopia. *Remote Sensing*, 15(4). <https://doi.org/10.3390/rs15041148>
- Lun, Y., Liu, L., Cheng, L., Li, X., Li, H., & Xu, Z. (2021). Assessment of GCMs simulation performance for precipitation and temperature from CMIP5 to CMIP6 over the Tibetan Plateau. *International Journal of Climatology*, 41(7), 3994–4018. <https://doi.org/10.1002/joc.7055>
- Madhuri, R., Raja, Y. S. L. S., Raju, K. S., Punith, B. S., & Manoj, K. (2021). Urban flood risk analysis of buildings using HEC-RAS 2D in climate change framework. *H2Open Journal*, 4(1), 262–275.
- Maghsood, F. F., Moradi, H., Bavani, A. R. M., Panahi, M., Berndtsson, R., & Hashemi, H. (2019). Climate change impact on flood frequency and source area in northern Iran under CMIP5 scenarios. *Water (Switzerland)*, 11(2), 1–22. <https://doi.org/10.3390/w11020273>
- Mahato, P. K., Singh, D., Bharati, B., Gagnon, A. S., Singh, B. B., & Brema, J. (2022). Assessing the impacts of human interventions and climate change on fluvial flooding using CMIP6 data and GIS-based hydrologic and hydraulic models. *Geocarto International*, 37(26), 11483–11508. <https://doi.org/10.1080/10106049.2022.2060311>
- Mananze, S., Pôças, I., & Cunha, M. (2020). Mapping and assessing the dynamics of shifting agricultural landscapes using google earth engine cloud computing, a case study in Mozambique. *Remote Sensing*, 12(8), 1–23. <https://doi.org/10.3390/RS12081279>
- Mann, H. B. (1945). Non-Parametric Test Against Trend. *Econometrica*, 13(3), 245–259. http://www.econometrist.com/node/18330371?story%7B_%7Ddid=18330371
- Mareuil, A., Leconte, R., Brissette, F., & Minville, M. (2007). Impacts of climate change on the frequency and severity of floods in the Châteauguay River basin, Canada. *Canadian Journal of Civil Engineering*, 34(9), 1048–1060. <https://doi.org/10.1139/L07-022>
- Mason, D. C., Speck, R., Devereux, B., Schumann, G. J.-P., Neal, J. C., & Bates, P. D. (2009). Flood detection in urban areas using TerraSAR-X. *IEEE Transactions on Geoscience and Remote Sensing*, 48(2), 882–894.

- Mekasha, A., Tesfaye, K., & Duncan, A. J. (2014). Trends in daily observed temperature and precipitation extremes over three Ethiopian eco-environments. *International Journal of Climatology*, 34(6), 1990–1999. <https://doi.org/10.1002/joc.3816>
- Mekonnen, K., Melesse, A. M., & Woldesenbet, T. A. (2022). Merging satellite rainfall estimates and daily rain gauge observations for improved flood simulation in MelkaKuntire catchment, upper Awash Basin, Ethiopia. *Remote Sensing Applications: Society and Environment*, 25, 100701.
- Mekuria, W., Mekonnen, K., Thorne, P., Bezabih, M., Tamene, L., & Abera, W. (2018). Competition for land resources: driving forces and consequences in crop-livestock production systems of the Ethiopian highlands. *Ecological Processes*, 7(1). <https://doi.org/10.1186/s13717-018-0143-7>
- Melkamu, T., Bagyaraj, M., Adimaw, M., & Ngusie, A. (2022). *Detecting and mapping flood inundation areas in Fogera-Dera Floodplain, Ethiopia during an extreme wet season using Sentinel-1 data*. 127(April 2021).
- Melton, F. (2015). NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP). Nasa, 1–8. https://cds.nccs.nasa.gov/wp-content/uploads/2015/06/NEX-GDDP_Tech_Note_v1_08June2015.pdf
- Mengistu, A. G., Woldesenbet, T. A., & Dile, Y. T. (2021). Evaluation of the performance of bias-corrected CORDEX regional climate models in reproducing Baro–Akobo basin climate. *Theoretical and Applied Climatology*, 144(1), 751–767.
- Mengistu, A. G., Woldesenbet, T. A., Dile, Y. T., Bayabil, H. K., & Tefera, G. W. (2023). Modeling impacts of projected land use and climate changes on the water balance in the Baro basin, Ethiopia. *Heliyon*, 9(3), e13965. <https://doi.org/10.1016/j.heliyon.2023.e13965>
- Mengistu, D., Bewket, W., Dosio, A., & Panitz, H.-J. (2021). Climate change impacts on water resources in the upper blue Nile (Abay) river basin, Ethiopia. *Journal of Hydrology*, 592, 125614.
- Meresa, H., Tischbein, B., & Mekonnen, T. (2022). Climate change impact on extreme precipitation and peak flood magnitude and frequency: observations from CMIP6 and hydrological models. In *Natural Hazards* (Vol. 111, Issue 3). Springer Netherlands. <https://doi.org/10.1007/s11069-021-05152-3>
- Mewded, M., Abebe, A., Tilahun, S., & Agide, Z. (2021). Impact of land use and land cover change on the magnitude of surface runoff in the endorheic Hayk Lake basin, Ethiopia. *SN Applied Sciences*, 3(8). <https://doi.org/10.1007/s42452-021-04725-y>
- Michelangeli, P. A., Vrac, M., & Loukos, H. (2009). Probabilistic downscaling approaches: Application to wind cumulative distribution functions. *Geophysical Research Letters*, 36(11), 1–6. <https://doi.org/10.1029/2009GL038401>
- Miller, J. D., & Hutchins, M. (2017). The impacts of urbanisation and climate change on urban flooding and urban water quality: A review of the evidence concerning the United Kingdom. *Journal of Hydrology: Regional Studies*, 12(June), 345–362. <https://doi.org/10.1016/j.ejrh.2017.06.006>
- Min, X., Yang, C., & Dong, N. (2020). Merging satellite and gauge rainfalls for flood forecasting of two catchments under different climate conditions. *Water (Switzerland)*, 12(3), 1–17. <https://doi.org/10.3390/w12030802>
- Minh, V. A., Quang, D. N., Tinh, N. X., & Ribbe, L. (2024). Spatio-temporal dynamics monitoring of surface water bodies in Nhat Le River Basin, Vietnam, by Google Earth Engine. *Journal of Water and Climate Change*, 15(3), 1262–1281. <https://doi.org/10.2166/wcc.2024.574>
- Mohamed, A., & Worku, H. (2020). Simulating urban land use and cover dynamics using cellular automata and Markov chain approach in Addis Ababa and the surrounding. *Urban Climate*, 31(August 2019), 100545. <https://doi.org/10.1016/j.uclim.2019.100545>
- Mohammed, J. A. (2024). Performance Evaluation and Ranking of CMIP6 Global Climate Models Over Upper Blue Nile (Abbay) Basin of Ethiopia. *Natural Hazards Research*.
- Mohammed, Y., Yimer, F., Tadesse, M., & Tesfaye, K. (2019). Variability and trends of rainfall extreme events in north east highlands of Ethiopia. *International Journal of Hydrology*, 2(5), 594–605. <https://doi.org/10.15406/ijh.2018.02.00131>
- Molini, A., Lanza, L. G., & La Barbera, P. (2005). The impact of tipping-bucket raingauge measurement errors on design rainfall for urban-scale applications. *Hydrological Processes: An International Journal*, 19(5), 1073–1088.
- Moriasi, D. N., Arnold, J. G., Van Liew, M. W., Bingner, R. L., Harmel, R. D., & Veith, T. L. (2007). Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. *Transactions of the ASABE*, 50(3), 885–900.
- Muluken Lebay. (2020). Techniques of Filling Missing Values of Daily and Monthly Rain Fall Data : A Review. *SF J Environ Earth Sci.*, 3(1), 1–5.
- Muñoz-Sabater, J., Dutra, E., Agustí-Panareda, A., Albergel, C., Arduini, G., Balsamo, G., Boussetta, S., Choulga, M., Harrigan, S., Hersbach, H., Martens, B., Miralles, D. G., Piles, M., Rodríguez-Fernández, N. J., Zsoter, E., Buontempo, C., & Thépaut, J. N. (2021). ERA5-Land: A state-of-the-art global reanalysis dataset for land applications. *Earth System Science Data*, 13(9), 4349–4383. <https://doi.org/10.5194/essd-13-4349-2021>
- Mzava, P., Valimba, P., & Nobert, J. (2021). Quantitative analysis of the impacts of climate and land-cover changes on urban flood runoffs: A case of dar es salaam, Tanzania. *Journal of Water and Climate Change*, 12(6), 2835–2853. <https://doi.org/10.2166/wcc.2021.026>

- Nash, J. E., & Sutcliffe, J. V. (1970). River flow forecasting through conceptual models part I—A discussion of principles. *Journal of Hydrology*, 10(3), 282–290.
- Nasiri, V., Deljouei, A., Moradi, F., Sadeghi, S. M. M., & Borz, S. A. (2022). Land Use and Land Cover Mapping Using Sentinel-2, Landsat-8 Satellite Images, and Google Earth Engine: A Comparison of Two Composition Methods. *Remote Sensing*, 14(9). <https://doi.org/10.3390/rs14091977>
- Navin, M. S., & Agilandeewari, L. (2020). Comprehensive review on land use/land cover change classification in remote sensing. *Journal of Spectral Imaging*, 9, 1–21. <https://doi.org/10.1255/jsi.2020.a8>
- Nawaz, N. R., Bellerby, T., Sayed, M., & Elshamy, M. (2010). Blue Nile runoff sensitivity to climate change. *Open Hydrology*, 4, 137–151.
- Neetu, & Ray, S. S. (2019). Exploring machine learning classification algorithms for crop classification using sentinel 2 data. *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences - ISPRS Archives*, 42(3/W6), 573–578. <https://doi.org/10.5194/isprs-archives-XLII-3-W6-573-2019>
- Negatu, T. A., Zimale, F. A., & Steenhuis, T. S. (2022). Establishing Stage–Discharge Rating Curves in Developing Countries: Lake Tana Basin, Ethiopia. *Hydrology*, 9(1), 1–26. <https://doi.org/10.3390/hydrology9010013>
- Nel, J. L., Le Maitre, D. C., Nel, D. C., Reyers, B., Archibald, S., Van Wilgen, B. W., Forsyth, G. G., Theron, A. K., O'Farrell, P. J., Mwenge Kahinda, J. M., Engelbrecht, F. A., Kapangaziwiri, E., Van Niekerk, L., & Barwell, L. (2014). Natural hazards in a changing world: A case for ecosystem-based management. *PLoS ONE*, 9(5). <https://doi.org/10.1371/journal.pone.0095942>
- Nghia, B. P. Q., Pal, I., Chollacoop, N., & Mukhopadhyay, A. (2022). Applying Google earth engine for flood mapping and monitoring in the downstream provinces of Mekong river. *Progress in Disaster Science*, 14(May), 100235. <https://doi.org/10.1016/j.pdisas.2022.100235>
- Nguyen, G. V., Le, X. H., Van, L. N., Jung, S., Yeon, M., & Lee, G. (2021). Application of random forest algorithm for merging multiple satellite precipitation products across South Korea. *Remote Sensing*, 13(20). <https://doi.org/10.3390/rs13204033>
- Nigusie, A. A., Shiferaw, K. M., & Ebrahim, S. E. (2021). Flood inundation modeling using HEC-RAS : the case of downstream Gumara river , Lake Tana sub basin , Ethiopia. *Geocarto International*, 0(0), 1–19. <https://doi.org/10.1080/10106049.2021.2022014>
- Nikiforov, A. M. (1994). Algorithm AS 288: Exact Smirnov two-sample tests for arbitrary distributions. *Journal of the Royal Statistical Society. Series C (Applied Statistics)*, 43(1), 265–270.
- Nobre, A. D., Cuartas, L. A., Momo, M. R., Severo, D. L., Pinheiro, A., & Nobre, C. A. (2016). HAND contour: a new proxy predictor of inundation extent. *Hydrological Processes*, 30(2), 320–333.
- Noël, T., Loukos, H., Defrance, D., Vrac, M., & Levavasseur, G. (2021). A high-resolution downscaled CMIP5 projections dataset of essential surface climate variables over the globe coherent with the ERA5 reanalysis for climate change impact assessments. *Data in Brief*, 35, 106900. <https://doi.org/10.1016/j.dib.2021.106900>
- Noi Phan, T., Kuch, V., & Lehnert, L. W. (2020). Land cover classification using google earth engine and random forest classifier-the role of image composition. *Remote Sensing*, 12(15), 1–22. <https://doi.org/10.3390/RS12152411>
- Noori, N., Kalin, L., Sen, S., Srivastava, P., & Lebleu, C. (2016). Identifying areas sensitive to land use/land cover change for downstream flooding in a coastal Alabama watershed. *Regional Environmental Change*, 16, 1833–1845.
- Notti, D., Giordan, D., Caló, F., Pepe, A., Zucca, F., & Galve, J. P. (2018). *Potential and Limitations of Open Satellite Data for Flood Mapping*, *Remote Sens.*, 10, 1673.
- O'Neill, B. C., Krieger, E., Ebi, K. L., Kemp-Benedict, E., Riahi, K., Rothman, D. S., Van Ruijven, B. J., Van Vuuren, D. P., Birkmann, J., & Kok, K. (2017). The roads ahead: Narratives for shared socioeconomic pathways describing world futures in the 21st century. *Global Environmental Change*, 42, 169–180.
- OCHA. (2019). *Eastern Africa Region (Regional Floods Snapshot)*. December, 2019. <https://reliefweb.int/report/south-sudan/eastern-africa-region-regional-flood-snapshot-november-2019>
- Ongdas, N., Akiyanova, F., Karakulov, Y., Muratbayeva, A., & Zinabdin, N. (2020). Application of hec-ras (2d) for flood hazard maps generation for yesil (ishim) river in kazakhstan. *Water (Switzerland)*, 12(10), 1–20. <https://doi.org/10.3390/w12102672>
- Otsu, N. (1975). A threshold selection method from gray-level histograms. *Automatica*, 11(285–296), 23–27.
- Otukei, J. R., & Blaschke, T. (2010). Land cover change assessment using decision trees, support vector machines and maximum likelihood classification algorithms. *International Journal of Applied Earth Observation and Geoinformation*, 12(SUPPL. 1), 27–31. <https://doi.org/10.1016/j.jag.2009.11.002>
- Ouled Sghaier, M., Hammami, I., Foucher, S., & Lepage, R. (2018). Flood extent mapping from time-series SAR images based on texture analysis and data fusion. *Remote Sensing*, 10(2), 237.
- Pachauri, R. K., Allen, M. R., Barros, V. R., Broome, J., Cramer, W., Christ, R., Church, J. A., Clarke, L., Dahe, Q., & Dasgupta, P. (2014). *Climate change 2014: synthesis report. Contribution of Working Groups I, II and III to the fifth assessment report of the Intergovernmental Panel on Climate Change*. Ipcc.
- Pandey, A. C., Kaushik, K., & Parida, B. R. (2022). Google Earth Engine for Large-Scale Flood Mapping Using SAR Data and Impact Assessment on Agriculture and Population of Ganga-Brahmaputra Basin. *Sustainability*

- (Switzerland), 14(7). <https://doi.org/10.3390/su14074210>
- Passah, A., Sur, S. N., Abraham, A., & Kandar, D. (2023). Synthetic Aperture Radar image analysis based on deep learning: A review of a decade of research. *Engineering Applications of Artificial Intelligence*, 123, 106305.
- Patakamuri, S. K., O'Brien, N., & Patakamuri, M. S. K. (2020). Package 'modifiedmk.' *Cran. R-Project*.
- Pekel, J.-F., Cottam, A., Gorelick, N., & Belward, A. S. (2016). High-resolution mapping of global surface water and its long-term changes. *Nature*, 540(7633), 418–422.
- Peng, X., Chen, S., Miao, Z., Xu, Y., Ye, M., & Lu, P. (2025). Automatic Flood Monitoring Method with SAR and Optical Data Using Google Earth Engine. *Water (Switzerland)*, 17(2). <https://doi.org/10.3390/w17020177>
- Perera, E. D. P., & Lahat, L. (2015). Fuzzy logic based flood forecasting model for the Kelantan River basin, Malaysia. *Journal of Hydro-Environment Research*, 9(4), 542–553.
- Pettitt, (1979). A Non-parametric to the Approach Problem. *Applied Statistics*, 28(2), 126–135.
- Piani, C., Haerter, J. O., & Coppola, E. (2010). Statistical bias correction for daily precipitation in regional climate models over Europe. *Theoretical and Applied Climatology*, 99(1–2), 187–192. <https://doi.org/10.1007/s00704-009-0134-9>
- Pohlert, T. (2016). Non-parametric trend tests and change-point detection. *CC BY-ND*, 4, 1–18.
- Pomerol, J.-C., & Barba-Romero, S. (2000). *Multicriterion decision in management: principles and practice* (Vol. 25). Springer Science & Business Media.
- Pontius, R. G., Shusas, E., & McEachern, M. (2004). Detecting important categorical land changes while accounting for persistence. *Agriculture, Ecosystems and Environment*, 101(2–3), 251–268. <https://doi.org/10.1016/j.agee.2003.09.008>
- Popp, A., Calvin, K., Fujimori, S., Havlik, P., Humpenöder, F., Stehfest, E., Bodirsky, B. L., Dietrich, J. P., Doelmann, J. C., Gusti, M., Hasegawa, T., Kyle, P., Obersteiner, M., Tabebu, A., Takahashi, K., Valin, H., Waldhoff, S., Weindl, I., Wise, M., ... Vuuren, D. P. va. (2017). Land-use futures in the shared socio-economic pathways. *Global Environmental Change*, 42, 331–345. <https://doi.org/10.1016/j.gloenvcha.2016.10.002>
- Psomiadis, E., Diakakis, M., & Soulis, K. X. (2020). Combining SAR and optical earth observation with hydraulic simulation for flood mapping and impact assessment. *Remote Sensing*, 12(23), 1–29. <https://doi.org/10.3390/rs12233980>
- Pulvirenti, L., Chini, M., Pierdicca, N., Guerriero, L., & Ferrazzoli, P. (2011). Flood monitoring using multi-temporal COSMO-SkyMed data: Image segmentation and signature interpretation. *Remote Sensing of Environment*, 115(4), 990–1002.
- Quirogaa, V. M., Kurea, S., Udoa, K., & Manoa, A. (2016). Application of 2D numerical simulation for the analysis of the February 2014 Bolivian Amazonia flood: Application of the new HEC-RAS version 5. *Ribagua*, 3(1), 25–33.
- Raju, K. S., & Kumar, D. N. (2020). Review of approaches for selection and ensembling of GCMS. *Journal of Water and Climate Change*, 11(3), 577–599. <https://doi.org/10.2166/wcc.2020.128>
- Rangari, V. A., Umamahesh, N. V., & Bhatt, C. M. (2019). Assessment of inundation risk in urban floods using HEC RAS 2D. *Modeling Earth Systems and Environment*, 5(4), 1839–1851.
- Redlands, C. (2011). ArcGIS desktop: release 10. *Environmental Systems Research Institute, CA*.
- Refaey, M. A., Mostafa, H., & Aboelkhear, M. (2019). Multi Criterion Decision Making Techniques for Ranking Regional climate models Over Wadi El-Natrun Catchment. *Australian Journal of Basic and Applied Sciences, March*. <https://doi.org/10.22587/ajbas.2019.13.5.9>
- Regasa, M. S., Nones, M., & Adeba, D. (2021). A review on land use and land cover change in Ethiopian basins. *Land*, 10(6), 585.
- Robinson, D., Zundel, A., Kramer, C., Nelson, R., deRosset, W., Hunt, J., Hogan, S., Lai, Y., & Aquaveo, L. L. C. (2019). *Two-Dimensional Hydraulic Modeling for Highways in the River Environment: Reference Document*. Federal Highway Administration (US).
- Ross, C. W., Prihodko, L., Anchang, J., Kumar, S., Ji, W., & Hanan, N. P. (2018). HYSOGs250m, global gridded hydrologic soil groups for curve-number-based runoff modeling. *Scientific Data*, 5(1), 1–9.
- Rouse, J. W., Haas, R. H., Schell, J. A., & Deering, D. W. (1974). Monitoring vegetation systems in the Great Plains with ERTS. *NASA Spec. Publ*, 351(1), 309.
- Ruben, G. B., Zhang, K., Dong, Z., & Xia, J. (2020). Analysis and projection of land-use/land-cover dynamics through scenario-based simulations using the CA-Markov model: A case study in guanting reservoir basin, China. *Sustainability*, 12(9). <https://doi.org/10.3390/su12093747>
- Saah, D., Johnson, G., Ashmall, B., Tondapu, G., Tenneson, K., Patterson, M., Poortinga, A., Markert, K., Quyen, N. H., San Aung, K., Schlichting, L., Matin, M., Uddin, K., Aryal, R. R., Dilger, J., Lee Ellenburg, W., Flores-Anderson, A. I., Wiell, D., Lindquist, E., ... Chishtie, F. (2019). Collect Earth: An online tool for systematic reference data collection in land cover and use applications. *Environmental Modelling and Software*, 118(March), 166–171. <https://doi.org/10.1016/j.envsoft.2019.05.004>
- Saghafian, B., Farazjoo, H., Bozorgy, B., & Yazdandoost, F. (2008). Flood intensification due to changes in land use. *Water Resources Management*, 22(8), 1051–1067. <https://doi.org/10.1007/s11269-007-9210-z>
- Saghafian, B., & Khosroshahi, M. (2005). Unit Response Approach for Priority Determination of Flood Source Areas.

- Journal of Hydrologic Engineering*, 10(4), 270–277. [https://doi.org/10.1061/\(asce\)1084-0699\(2005\)10:4\(270\)](https://doi.org/10.1061/(asce)1084-0699(2005)10:4(270))
- Saksena, S., Merwade, V., & Singhofen, P. J. (2019). Flood inundation modeling and mapping by integrating surface and subsurface hydrology with river hydrodynamics. *Journal of Hydrology*, 575(June), 1155–1177. <https://doi.org/10.1016/j.jhydrol.2019.06.024>
- Samie, A., Deng, X., Jia, S., & Chen, D. (2017). Scenario-based simulation on dynamics of land-use-land-cover change in Punjab province, Pakistan. *Sustainability*, 9(8). <https://doi.org/10.3390/su9081285>
- Sanyal, J., Densmore, A. L., & Carbonneau, P. (2014). Analysing the effect of land-use/cover changes at sub-catchment levels on downstream flood peaks: A semi-distributed modelling approach with sparse data. *Catena*, 118, 28–40. <https://doi.org/10.1016/j.catena.2014.01.015>
- Sayadi, A., Beydokhti, N. T., Najarchi, M., & Najafizadeh, M. M. (2019). Investigation into the Effects of Climatic Change on Temperature, Rainfall, and Runoff of the Doroudzan Catchment, Iran, Using the Ensemble Approach of CMIP3 Climate Models. *Advances in Meteorology*, 2019. <https://doi.org/10.1155/2019/6357912>
- Seleshi, Y., & Zanke, U. (2004). Recent changes in rainfall and rainy days in Ethiopia. *International Journal of Climatology*, 24(8), 973–983. <https://doi.org/10.1002/joc.1052>
- Sen, P. K. (1968). Estimates of the Regression Coefficient Based on Kendall ' s Tau Author (s): Pranab Kumar Sen Source : Journal of the American Statistical Association , Vol . 63 , No . 324 (Dec . , 1968), pp . Published by : Taylor & Francis , Ltd . on behalf of the A. *Journal of the American Statistical Association*, 63(324), 1379–1389. <https://www.jstor.org/stable/2285891>
- Senent-Aparicio, J., Pérez-Sánchez, J., Carrillo-García, J., & Soto, J. (2017). Using SWAT and fuzzy TOPSIS to assess the impact of climate change in the headwaters of the Segura River Basin (SE Spain). *Water (Switzerland)*, 9(2). <https://doi.org/10.3390/w9020149>
- Sewnet, A., & Abebe, G. (2018). Land use and land cover change and implication to watershed degradation by using GIS and remote sensing in the Koga watershed, North Western Ethiopia. *Earth Science Informatics*, 11(1), 99–108. <https://doi.org/10.1007/s12145-017-0323-5>
- Shafizadeh-Moghadam, H., Khazaei, M., Alavipanah, S. K., & Weng, Q. (2021). Google Earth Engine for large-scale land use and land cover mapping: an object-based classification approach using spectral, textural and topographical factors. *GIScience and Remote Sensing*, 58(6), 914–928. <https://doi.org/10.1080/15481603.2021.1947623>
- Shah, A. A., Ye, J., Abid, M., & Ullah, R. (2017). Determinants of flood risk mitigation strategies at household level: a case of Khyber Pakhtunkhwa (KP) province, Pakistan. *Natural Hazards*, 88(1), 415–430. <https://doi.org/10.1007/s11069-017-2872-9>
- Sharma, A., & Kale, G. D. (2022). Ranking of general circulation models for Surat City by using a hybrid approach. *Water Practice and Technology*, 17(10), 2186–2198. <https://doi.org/10.2166/wpt.2022.118>
- Shi, Y., Chen, C., Chen, J., Mohammadi, B., Cheraghalizadeh, M., Abdallah, M., Mert Katipoğlu, O., Li, H., & Duan, Z. (2023). Evaluation of the RF-MEP Method for Merging Multiple Gridded Precipitation Products in the Chongqing City, China. *Remote Sensing*, 15(17). <https://doi.org/10.3390/rs15174230>
- Shiru, M. S., Shahid, S., Chung, E. S., Alias, N., & Scherer, L. (2019). A MCDM-based framework for selection of general circulation models and projection of spatio-temporal rainfall changes: A case study of Nigeria. *Atmospheric Research*, 225(December 2018), 1–16. <https://doi.org/10.1016/j.atmosres.2019.03.033>
- Shoyama, K. (2021). Assessment of land-use scenarios at a national scale using intensity analysis and figure of merit components. *Land*, 10(4). <https://doi.org/10.3390/land10040379>
- Singh, A., Dawson, D., Trigg, M., & Wright, N. (2021). A review of modelling methodologies for flood source area (FSA) identification. *Natural Hazards*, 107(2), 1047–1068. <https://doi.org/10.1007/s11069-021-04672-2>
- Singh, G., & Rawat, K. S. (2024). Mapping flooded areas utilizing Google Earth Engine and open SAR data: a comprehensive approach for disaster response. *Discover Geoscience*, 2(1). <https://doi.org/10.1007/s44288-024-00006-4>
- Singh, V. P. (2019). *Impact of Climate Change on Water Resources: With Modeling Techniques and Case Studies*. ASCE-AMER SOC CIVIL ENGINEERS 1801 ALEXANDER BELL DR, RESTON, VA 20191-4400 USA.
- Sinshaw, B. G., Kindie, A., & Atinkut, H. B. (2018). *Analysis of regional flood frequency and its socio- economic impact in Ethiopia*. 12(May 2020). <https://doi.org/10.5897/AJEST2018.xxxx>
- Sisay, G., Gesesse, B., Fürst, C., Kassie, M., & Kebede, B. (2023). Modeling of land use/land cover dynamics using artificial neural network and cellular automata Markov chain algorithms in Goang watershed, Ethiopia. *Heliyon*, 9(9), e20088. <https://doi.org/10.1016/j.heliyon.2023.e20088>
- Song, L., Song, C., Luo, S., Chen, T., Liu, K., Li, Y., Jing, H., & Xu, J. (2021). Refining and densifying the water inundation area and storage estimates of Poyang Lake by integrating Sentinel-1/2 and bathymetry data. *International Journal of Applied Earth Observation and Geoinformation*, 105, 102601. <https://doi.org/10.1016/j.jag.2021.102601>
- Song, X., Zhang, J., Zhan, C., Xuan, Y., Ye, M., & Xu, C. (2015). Global sensitivity analysis in hydrological modeling: Review of concepts, methods, theoretical framework, and applications. *Journal of Hydrology*, 523(225), 739–757. <https://doi.org/10.1016/j.jhydrol.2015.02.013>
- Soriano, E., Mediero, L., & Garijo, C. (2019). Selection of bias correction methods to assess the impact of climate

- change on flood frequency curves. *Water (Switzerland)*, 11(11). <https://doi.org/10.3390/w11112266>
- SPIDER, U. N. (2019). *Step-by-Step: Recommended Practice: Flood Mapping and Damage Assessment Using Sentinel-1 SAR Data in Google Earth Engine* | UN-SPIDER Knowledge Portal.
- Srinivasa Raju, K., & Nagesh Kumar, D. (2015). Ranking general circulation models for India using TOPSIS. *Journal of Water and Climate Change*, 6(2), 288–299. <https://doi.org/10.2166/wcc.2014.074>
- Srinivasa Raju, K., Sonali, P., & Nagesh Kumar, D. (2017). Ranking of CMIP5-based global climate models for India using compromise programming. *Theoretical and Applied Climatology*, 128(3–4), 563–574. <https://doi.org/10.1007/s00704-015-1721-6>
- Stephens, M. A. (1974). EDF statistics for goodness of fit and some comparisons. *Journal of the American Statistical Association*, 69(347), 730–737.
- Stromann, O., Nascetti, A., Yousif, O., & Ban, Y. (2020). Dimensionality Reduction and Feature Selection for Object-Based Land Cover Classification based on Sentinel-1 and Sentinel-2 Time Series Using Google Earth Engine. *Remote Sensing*, 12(1). <https://doi.org/10.3390/RS12010076>
- Szuster, B. W., Chen, Q., & Borger, M. (2011). A comparison of classification techniques to support land cover and land use analysis in tropical coastal zones. *Applied Geography*, 31(2), 525–532. <https://doi.org/10.1016/j.apgeog.2010.11.007>
- Tabari, H. (2020). Climate change impact on flood and extreme precipitation increases with water availability. *Scientific Reports*, 10(1), 1–11. <https://doi.org/10.1038/s41598-020-70816-2>
- Tadese, S., Soromessa, T., & Bekele, T. (2021). Analysis of the Current and Future Prediction of Land Use/Land Cover Change Using Remote Sensing and the CA-Markov Model in Majang Forest Biosphere Reserves of Gambella, Southwestern Ethiopia. *Scientific World Journal*, 2021. <https://doi.org/10.1155/2021/6685045>
- Talukdar, S., Singha, P., Mahato, S., Shahfahad, Pal, S., Liou, Y. A., & Rahman, A. (2020). Land-use land-cover classification by machine learning classifiers for satellite observations-A review. *Remote Sensing*, 12(7). <https://doi.org/10.3390/rs12071135>
- Tan, M. L., Samat, N., Chan, N. W., Lee, A. J., & Li, C. (2019). Analysis of precipitation and temperature extremes over the Muda River Basin, Malaysia. *Water (Switzerland)*, 11(2), 1–16. <https://doi.org/10.3390/w11020283>
- Tang, B., Hu, W., & Duan, A. (2021). Assessment of extreme precipitation indices over Indochina and South China in CMIP6 models. *Journal of Climate*, 34(18), 7507–7524. <https://doi.org/10.1175/JCLI-D-20-0948.1>
- Tanim, A. H., McRae, C. B., Tavakol-Davani, H., & Goharian, E. (2022). Flood detection in urban areas using satellite imagery and machine learning. *Water*, 14(7), 1140.
- Tank, A., Zwiers, F., & Zhang, X. (2009). Guidelines on Analysis of extremes in a changing climate. *World Meteorological Organization*, 72. http://www.wmo.int/pages/prog/wcp/wcdmp/wcdmp_series/documents/WCDMP_72_TD_1500_en__1.pdf
- Tassew, B. G., Belete, M. A., & Miegel, K. (2019). Application of HEC-HMS model for flow simulation in the Lake Tana basin: The case of Gilgel Abay catchment, upper Blue Nile basin, Ethiopia. *Hydrology*, 6(1), 21.
- Tassi, A., & Vizzari, M. (2020). Object-oriented lulc classification in google earth engine combining snic, glcm, and machine learning algorithms. *Remote Sensing*, 12(22), 1–17. <https://doi.org/10.3390/rs12223776>
- Tay, C. W. J., Yun, S. H., Chin, S. T., Bhardwaj, A., Jung, J., & Hill, E. M. (2020). Rapid flood and damage mapping using synthetic aperture radar in response to Typhoon Hagibis, Japan. *Scientific Data*, 7(1), 1–9. <https://doi.org/10.1038/s41597-020-0443-5>
- Taye, M. T., & Dyer, E. (2024). Hydrologic Extremes in a Changing Climate: a Review of Extremes in East Africa. *Current Climate Change Reports*, 10(1), 1–11. <https://doi.org/10.1007/s40641-024-00193-9>
- Taylor, K. E. (2001). Summarizing multiple aspects of model performance in a single diagram. *Journal of Geophysical Research: Atmospheres*, 106(D7), 7183–7192.
- Taylor, K. E., Stouffer, R. J., & Meehl, G. A. (2012). An overview of CMIP5 and the experiment design. *Bulletin of the American Meteorological Society*, 93(4), 485–498. <https://doi.org/10.1175/BAMS-D-11-00094.1>
- Te Chow, V. (1959). *Open channel hydraulics*.
- Tefera, B., & Kassa, H. (2017). Trends and driving forces of Eucalyptus plantation by smallholders in the Lake Tana Watershed of Ethiopia. *Social and Ecological System Dynamics: Characteristics, Trends, and Integration in the Lake Tana Basin, Ethiopia*, 563–580.
- Tegegne, G., & Melesse, A. M. (2020). Multimodel ensemble projection of hydro-climatic extremes for climate change impact assessment on water resources. *Water Resources Management*, 34(9), 3019–3035.
- Tegegne, G., Melesse, A. M., & Alamirew, T. (2021). Projected changes in extreme precipitation indices from CORDEX simulations over Ethiopia, East Africa. *Atmospheric Research*, 247(July 2020), 105156. <https://doi.org/10.1016/j.atmosres.2020.105156>
- Tegegne, G., Melesse, A. M., Asfaw, D. H., & Worqlul, A. W. (2020). Flood frequency analyses over different basin scales in the Blue Nile River Basin, Ethiopia. *Hydrology*, 7(3). <https://doi.org/10.3390/HYDROLOGY7030044>
- Teklay, A., Dile, Y. T., Asfaw, D. H., Bayabil, H. K., & Sisay, K. (2021). Impacts of climate and land use change on hydrological response in Gumara Watershed, Ethiopia. *Ecohydrology & Hydrobiology*, 21(2), 315–332.
- Tenfie, H. W., Saathoff, F., Hailu, D., & Gebissa, A. (2022). Selection of Representative General Circulation Models for

- Climate Change Study Using Advanced Envelope-Based and Past Performance Approach on Transboundary River Basin, a Case of Upper Blue Nile Basin, Ethiopia. *Sustainability (Switzerland)*, 14(4).
<https://doi.org/10.3390/su14042140>
- Teutschbein, C., & Seibert, J. (2012). Bias correction of regional climate model simulations for hydrological climate-change impact studies: Review and evaluation of different methods. *Journal of Hydrology*, 456–457, 12–29.
<https://doi.org/10.1016/j.jhydrol.2012.05.052>
- Thakur, B., Parajuli, R., Kalra, A., Ahmad, S., & Gupta, R. (2017). Coupling HEC-RAS and HEC-HMS in Precipitation Runoff Modelling and Evaluating Flood Plain Inundation Map. *World Environmental and Water Resources Congress 2017: Hydraulics and Waterways and Water Distribution Systems Analysis - Selected Papers from the World Environmental and Water Resources Congress 2017*, 240–251. <https://doi.org/10.1061/9780784480625.022>
- Thanh Noi, P., & Kappas, M. (2017). Comparison of Random Forest, k-Nearest Neighbor, and Support Vector Machine Classifiers for Land Cover Classification Using Sentinel-2 Imagery. *Sensors (Basel, Switzerland)*, 18(1).
<https://doi.org/10.3390/s18010018>
- Thrasher, B., Wang, W., Michaelis, A., Melton, F., Lee, T., & Nemani, R. (2022). NASA Global Daily Downscaled Projections, CMIP6. *Scientific Data*, 9(1), 1–7. <https://doi.org/10.1038/s41597-022-01393-4>
- Tibangayuka, N., Mulungu, D. M. M., & Izdori, F. (2022). Assessing the potential impacts of climate change on streamflow in the data-scarce Upper Ruvu River watershed, Tanzania. *Journal of Water and Climate Change*, 13(9), 3496–3513. <https://doi.org/10.2166/wcc.2022.208>
- Tikuye, B. G., Rusnak, M., Manjunatha, B. R., & Jose, J. (2023). Land use and land cover change detection using the random forest approach: the case of the Upper Blue Nile River Basin, Ethiopia. *Global Challenges*, 7(10), 2300155.
- Tiwari, V., Kumar, V., Matin, M. A., Thapa, A., Ellenburg, W. L., Gupta, N., & Thapa, S. (2020). Flood inundation mapping-Kerala 2018; Harnessing the power of SAR, automatic threshold detection method and Google Earth Engine. *PLoS ONE*, 15(8 August), 1–17. <https://doi.org/10.1371/journal.pone.0237324>
- Tolessa, T., Dechassa, C., Simane, B., Alamerew, B., & Kidane, M. (2020). Land use/land cover dynamics in response to various driving forces in Didessa sub-basin, Ethiopia. *GeoJournal*, 85(3), 747–760. <https://doi.org/10.1007/s10708-019-09990-4>
- Toride, K., Cawthorne, D. L., Ishida, K., Kavvas, M. L., & Anderson, M. L. (2018). Long-term trend analysis on total and extreme precipitation over Shasta Dam watershed. *Science of the Total Environment*, 626, 244–254.
<https://doi.org/10.1016/j.scitotenv.2018.01.004>
- Tschöke, G. V., Kruk, N. S., de Queiroz, P. I. B., Chou, S. C., & de Sousa Junior, W. C. (2017). Comparison of two bias correction methods for precipitation simulated with a regional climate model. *Theoretical and Applied Climatology*, 127(3–4), 841–852. <https://doi.org/10.1007/s00704-015-1671-z>
- Tsubaki, R., & Kawahara, Y. (2013). The uncertainty of local flow parameters during inundation flow over complex topographies with elevation errors. *Journal of Hydrology*, 486, 71–87.
<https://doi.org/10.1016/j.jhydrol.2013.01.042>
- Tupas, M. E., Roth, F., Bauer-Marschallinger, B., & Wagner, W. (2023). An intercomparison of Sentinel-1 based change detection algorithms for flood mapping. *Remote Sensing*, 15(5), 1200.
- Twele, A., Cao, W., Plank, S., & Martinis, S. (2016). Sentinel-1-based flood mapping: a fully automated processing chain. *International Journal of Remote Sensing*, 37(13), 2990–3004.
- Tzeng, G.-H., & Huang, J.-J. (2011). *Multiple attribute decision making: methods and applications*. CRC press.
- USACE. (2000). Hydrologic Modeling System. *Hydrologic Modeling System HEC-HMS Technical Reference Manual*, March, 158.
- USACE. (2008). Hydrologic Modeling System User 's Manual. *Transform*, September, 290.
- USACE. (2016). *HEC-RAS 5.0 Reference Manual.pdf*.
- Van Liew, M. W., Veith, T. L., Bosch, D. D., & Arnold, J. G. (2007). Suitability of SWAT for the conservation effects assessment project: comparison on USDA agricultural research service watersheds. *Journal of Hydrologic Engineering*, 12(2), 173–189.
- Van Vuuren, D. P., Kok, M. T. J., Girod, B., Lucas, P. L., & de Vries, B. (2012). Scenarios in global environmental assessments: key characteristics and lessons for future use. *Global Environmental Change*, 22(4), 884–895.
- Vashist, K., & Singh, K. K. (2023). HEC-RAS 2D modeling for flood inundation mapping: a case study of the Krishna River Basin. *Water Practice & Technology*, 18(4), 831–844.
- Vila, D. A., de Goncalves, L. G. G., Toll, D. L., & Rozante, J. R. (2009). Statistical evaluation of combined daily gauge observations and rainfall satellite estimates over continental South America. *Journal of Hydrometeorology*, 10(2), 533–543. <https://doi.org/10.1175/2008JHM1048.1>
- Vu, T. T., & Shen, Y. (2021). Land-use and land-cover changes in dong trieu district, vietnam, during past two decades and their driving forces. *Land*, 10(8). <https://doi.org/10.3390/land10080798>
- Wagena, M. B., Sommerlot, A., Abiy, A. Z., Collick, A. S., Langan, S., Fuka, D. R., & Easton, Z. M. (2016). Climate change in the Blue Nile Basin Ethiopia: implications for water resources and sediment transport. *Climatic Change*, 139, 229–243.

- Waghaye, A. M., Rajwade, Y. A., Randhe, R. D., & Kumari, N. (2018). Trend analysis and change point detection of rainfall of Andhra Pradesh and Telangana, India. *Journal of Agrometeorology*, 20(2), 160–163.
- Wang, C., Shang, S., Jia, D., Han, Y., Sauvage, S., Sánchez-Pérez, J. M., Kuramochi, K., & Hatano, R. (2018). Integrated effects of land use and topography on streamflow response to precipitation in an agriculture-forest dominated northern watershed. *Water (Switzerland)*, 10(5). <https://doi.org/10.3390/w10050633>
- Wang, D., Liu, J., Wang, H., Shao, W., Mei, C., & Ding, X. (2022). Performance evaluations of CMIP6 and CMIP5 models for precipitation simulation over the Hanjiang River Basin, China. *Journal of Water and Climate Change*, 13(5), 2089–2106. <https://doi.org/10.2166/wcc.2022.402>
- Wang, L., Chen, S., Zhu, W., Ren, H., Zhang, L., & Zhu, L. (2021). Spatiotemporal variations of extreme precipitation and its potential driving factors in China's North-South Transition Zone during 1960–2017. *Atmospheric Research*, 252(January), 105429. <https://doi.org/10.1016/j.atmosres.2020.105429>
- Worku, G., Teferi, E., Bantider, A., & Dile, Y. T. (2019). Observed changes in extremes of daily rainfall and temperature in Jemma Sub-Basin, Upper Blue Nile Basin, Ethiopia. *Theoretical and Applied Climatology*, 135(3–4), 839–854. <https://doi.org/10.1007/s00704-018-2412-x>
- Worku, G., Teferi, E., Bantider, A., Dile, Y. T., & Taye, M. T. (2018). Evaluation of regional climate models performance in simulating rainfall climatology of Jemma sub-basin, Upper Blue Nile Basin, Ethiopia. *Dynamics of Atmospheres and Oceans*, 83, 53–63. <https://doi.org/10.1016/j.dynatmoce.2018.06.002>
- Wubie, M. A., Assen, M., & Nicolau, M. D. (2016). Patterns , causes and consequences of land use / cover dynamics in the Gumara watershed of lake Tana basin , Northwestern Ethiopia. *Environmental Systems Research*, 1–13. <https://doi.org/10.1186/s40068-016-0058-1>
- Xiong, J., Thenkabail, P. S., Tilton, J. C., Gumma, M. K., Teluguntla, P., Oliphant, A., Congalton, R. G., Yadav, K., & Gorelick, N. (2017). Nominal 30-m cropland extent map of continental Africa by integrating pixel-based and object-based algorithms using Sentinel-2 and Landsat-8 data on google earth engine. *Remote Sensing*, 9(10), 1–27. <https://doi.org/10.3390/rs9101065>
- Yadav, A., Singh, R. M., Pandey, M. K., Maurya, S. P., & Singh, S. K. (2024). Hydrodynamic modelling of river training works for protection of group of villages on the left bank of Ramganga River: a case study. *Natural Hazards*. <https://doi.org/10.1007/s11069-024-06888-4>
- Yalcin, E. (2024). Assessing future changes in flood frequencies under CMIP6 climate projections using SWAT modeling: a case study of Bitlis Creek, Turkey. *Journal of Water and Climate Change*, 15(5), 2212–2231. <https://doi.org/10.2166/wcc.2024.646>
- Yamamoto, K., Sayama, T., & Apip. (2021). Impact of climate change on flood inundation in a tropical river basin in Indonesia. *Progress in Earth and Planetary Science*, 8(1). <https://doi.org/10.1186/s40645-020-00386-4>
- Yan, R., Huang, J., Wang, Y., Gao, J., & Qi, L. (2016). Modeling the combined impact of future climate and land use changes on streamflow of Xinjiang Basin, China. *Hydrology Research*, 47(2), 356–372. <https://doi.org/10.2166/nh.2015.206>
- Yang, S., Yang, D., Zhao, B., Ma, T., Lu, W., & Santisirisomboon, J. (2022). Future Changes in High and Low Flows under the Impacts of Climate and Land Use Changes in the Jiulong River Basin of Southeast China. *Atmosphere*, 13(2). <https://doi.org/10.3390/atmos13020150>
- Yang, Z., Hsu, K., Sorooshian, S., Xu, X., Braithwaite, D., Zhang, Y., & Verbist, K. M. J. (2017). Merging high-resolution satellite-based precipitation fields and point-scale rain gauge measurements-A case study in Chile. *Journal of Geophysical Research*, 122(10), 5267–5284. <https://doi.org/10.1002/2016JD026177>
- Yesuph, A. Y., & Dagnew, A. B. (2019). Land use/cover spatiotemporal dynamics, driving forces and implications at the Beshillo catchment of the Blue Nile Basin, North Eastern Highlands of Ethiopia. *Environmental Systems Research*, 8(1). <https://doi.org/10.1186/s40068-019-0148-y>
- Yilma, A. D., & Awulachew, S. B. (2009). *Characterization and Atlas of the Blue Nile Basin and its Sub basins*.
- Yilma, Z. L., & Kebede, H. H. (2023). Simulation of the rainfall-runoff relationship using an HEC-HMS hydrological model for Dabus Subbasin, Blue Nile Basin, Ethiopia. *H2Open Journal*, 6(3), 331–342. <https://doi.org/10.2166/h2oj.2023.055>
- Yisehak, B. (2021). Prediction of flood frequency under a changing climate, the case of Hare watershed, Rift Valley Basin of Ethiopia. *Sustainable Water Resources Management*, 7(1), 1–15. <https://doi.org/10.1007/s40899-021-00492-1>
- Yuan, D. (1999). Survey of multispectral methods for land-cover change analysis. *Remote Sensing Change Detection: Environmental Monitoring Methods and Application*.
- Yue, S., Pilon, P., Phinney, B., & Cavadias, G. (2002). The influence of autocorrelation on the ability to detect trend in hydrological series. *Hydrological Processes*, 16(9), 1807–1829. <https://doi.org/10.1002/hyp.1095>
- Zelew, D. G., & Melesse, A. M. (2018). Applicability of a spatially semi-distributed hydrological model for watershed scale runoff estimation in Northwest Ethiopia. *Water*, 10(7), 923.
- Zhang, X., Yang, F., & others. (2004). RCLimDex (1.0) user manual. *Climate Research Branch Environment Canada*, 22.
- Zhao, M., Ling, Q., & Li, F. (2018). An iterative feedback-based change detection algorithm for flood mapping in SAR images. *IEEE Geoscience and Remote Sensing Letters*, 16(2), 231–235.

Zinabie, A., & Kebede, B. (2020). Hydraulic Analysis of Storm Water Drainage System in Alamata Town, South Tigray, Ethiopia. *Iranian Journal of Energy and Environment*, 11(1), 40–50. <https://doi.org/10.5829/ijee.2020.11.01.07>

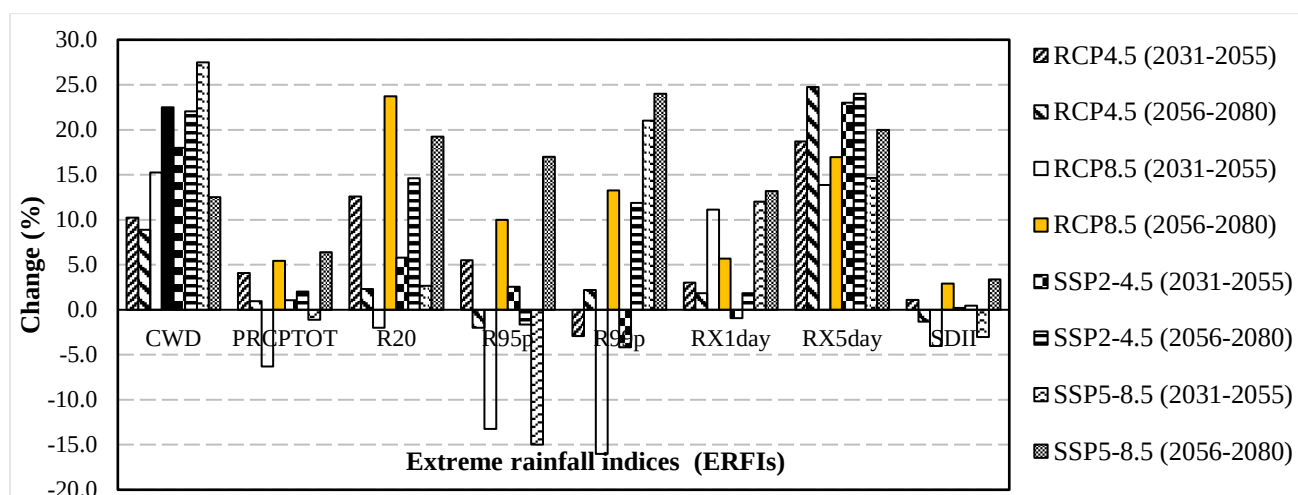
Appendix

A1: Location, elevation, and long-term mean annual rainfall of ground-based rainfall stations located in the UBN basin of Ethiopia from 1981 to 2019. In the table, the hash symbol (#) indicates a rainfall station used for training during the merging process.

No.	Rainfall station	Latitude (°)	Longitude (°)	Elevation (m) amsl	Mean annual rainfall (mm)
1	Ambo	9.00	37.80	2068	1021
2	Amed Ber	11.91	37.88	2051	1360
3	Assosa	10.20	34.80	1600	1152
4	Bahir Dar [#]	11.60	37.30	1827	1359
5	Bullen	10.30	35.80	1659	1091
6	Chagni [#]	10.60	36.50	1614	1421
7	Dangila	11.20	36.60	2116	1516
8	Debre Berhan [#]	9.60	39.50	2750	1046
9	Debre Markos	10.30	37.50	2446	1293
10	Debre Tabor	11.87	38.01	2612	1509
11	Dembi	8.10	36.50	1925	1975
12	Dessie	11.12	39.51	2521	1281
13	Gassay	11.79	38.13	2789	1483
14	Gohatsion	10.00	38.20	2507	1147
15	Gondar [#]	12.50	37.40	1973	1214
16	Gorgora [#]	12.20	37.30	2100	1403
17	Guba	11.00	35.20	1360	1168
18	Guduru	9.63	37.48	1827	1316
19	Limu Seka	9.90	36.60	1398	1246
20	Mehal Meda	10.30	39.50	3084	1143
21	Mekane Selam [#]	10.70	38.80	2605	1244
22	Mekaneyesus	11.58	37.90	2374	1380
23	Motta	11.20	38.10	2417	1515
24	Nedjo	9.50	35.50	1970	1739
25	Nekemte [#]	9.10	36.50	2080	2139
26	Wanzaye	11.78	37.68	1821	1439
27	Wereta	11.92	37.70	1819	1372

A2: Weights of performance measures (R, RMSE, PBIAS)

ERFI	CMIP5			CMIP6		
	R	RMSE	PBIAS	R	RMSE	PBIAS
CWD	0.44	0.36	0.20	0.39	0.39	0.22
PRCPTOT	0.25	0.42	0.33	0.32	0.33	0.35
R20	0.39	0.35	0.26	0.40	0.33	0.27
R95p	0.39	0.25	0.36	0.37	0.41	0.22
R99p	0.31	0.30	0.39	0.41	0.30	0.29
RX1 day	0.41	0.26	0.33	0.41	0.28	0.31
RX5 day	0.43	0.21	0.36	0.43	0.24	0.33
SDII	0.48	0.25	0.27	0.29	0.44	0.27
Monthly RF	0.44	0.29	0.27	0.48	0.25	0.27



A3: Changes in projected extreme rainfall indices in the study basin relative the baseline period (1981–2005).

A4: M-K trend Z statistics and slope for the average extreme rainfall indices projected using: (a) CMIP5-ensemble and (b) CMIP5-ensemble

(a) CMIP5- ensemble								
ERFI	RCP4.5 (2031-2060)		RCP4.5 (2061-2090)		RCP8.5 (2031-2060)		RCP8.5 (2061-2090)	
	Z	Slope	Z	Slope	Z	Slope	Z	Slope
CWD	-0.27	-0.09	0.46	-0.08	1.66↑↑	0.64	-0.67	-0.11
PRCPTOT	-0.11	0.62	-0.52	-0.76	1.35	5.63	1.06	15.77
R20	-0.33	-0.09	-0.34	-0.45	1.56	0.45	1.26	0.43
R95p	0.09	0.58	0.42	0.75	0.34	0.65	1.34	7.90
R99p	-0.01	0.24	1.46	1.97	0.67	0.67	1.99↑↑	5.22
RX1day	-0.41	-0.33	1.98↑↑	0.47	0.58	0.09	1.88↑	0.29
RX5day	-0.41	-0.21	0.62	0.95	0.42	0.07	1.40	1.87
SDII	-0.82	-0.07	0.72	0.74	0.99	0.07	1.83↑	0.08
(b) CMIP6-ensemble								
ERFI	SSP2-4.5 (2031-2060)		SSP2-4.5 (2061-2090)		SSP5-8.5 (2031-2060)		SSP5-8.5 (2061-2090)	
	Z	Slope	Z	Slope	Z	Slope	Z	Slope
CWD	0.61	0.09	0.42	0.08	0.92	0.13	-1.69↓	-0.36
PRCPTOT	-0.43	-4.83	0.76	8.96	1.54↑	8.12	0.78	8.35
R20	-0.88	-0.18	0.49	0.20	0.99	0.21	0.86	0.58
R95p	-0.24	3.25	0.46	4.35	1.59	4.45	0.09	-0.11
R99p	-0.67	-2.31	0.44	2.57	0.81	0.17	0.03	0.72
RX1day	-0.44	-0.11	0.27	0.36	1.33	0.15	0.31	0.31
RX5day	-0.91	-0.23	0.22	1.13	1.85↑	1.46	-0.16	-0.06
SDII	-0.34	-0.11	0.67	0.02	0.46	0.05	-0.04	-0.03

In the above Tables above, ↑↑ and ↓↓ indicate significant positive and negative trends, respectively

A5: Coefficient of variation of extreme rainfall indices for the future period's under the RCP and SSP scenarios

	CWD	PRCPTOT	R20	R95p	R99p	RX1day	RX5day	SDII
RCP4.5 (2031-2055)	19.7	6.3	11.6	18.4	40.7	6.6	6.3	3.6
RCP4.5 (2056-2080)	14.7	7.1	9.2	37.8	60	9.6	18.7	8.4
RCP8.5 (2031-2055)	22.1	7.1	15.8	37.9	88.4	16.6	7.9	9.0
RCP8.5 (2056-2080)	24.1	6.8	14.1	30.3	56.8	8.9	5.2	5.9
SSP2-4.5 (2031-2055)	6.4	9.8	23.5	49.4	88.9	21.7	9.9	10.6
SSP2-4.5 (2056-2080)	4.0	11.1	21.0	51.2	86.3	26.1	25.1	11.0
SSP5-8.5 (2031-2055)	7.2	7.5	28.7	39.2	82.9	13.3	11.0	9.00
SSP5-8.5 (2056-2080)	13.4	12.4	16.5	49.3	74.9	18.2	16.3	10.6

B1: Confusion matrix for 1985

LULC class	Forest	Shrubland	Grassland	cultivated land	Settlement	Row total (RT)	User accuracy (UA) (%)	RT/Total
Forest	53	13	0	1	0	67	79.10	0.1252
Shrubland	1	88	0	4	0	93	94.62	0.1738
Grassland	2	0	100	3	0	105	95.24	0.1963
cultivated land	0	2	1	216	2	221	97.74	0.4131
Settlement	0	0	0	1	48	49	97.96	0.0916
Column total (CT)	56	103	101	225	50	535		
Producer accuracy (PA) (%)	94.64	85.44	99.01	96.00	96.00			
CT/Total	0.1047	0.1925	0.1888	0.4206	0.0935			
Sum of (CT/Total)*(RT/Total)	0.2659							
Overall accuracy (OA)	0.9439	Overall accuracy (OA) (%)			94.39			
Kappa (K)	0.9236							

B2: Confusion matrix for 2000

LULC class	Forest	Shrubland	Grassland	cultivated land	Settlement	Row total (RT)	User accuracy (UA) (%)	RT/Total
Forest	65	0	0	0	0	65	100.00	0.0959
Shrubland	0	79	0	6	0	85	92.94	0.1254
Grassland	0	1	182	13	0	196	92.86	0.2891
cultivated land	0	1	11	270	0	282	95.74	0.4159
Settlement	0	0	0	3	47	50	94.00	0.0737
Column total (CT)	65	81	193	292	47	678		
Producer accuracy (PA) (%)	100.00	97.53	94.30	92.47	100.00			
CT/Total	0.0959	0.1195	0.2847	0.4307	0.0693			
Sum of (CT/Total)*(RT/Total)	0.2907							
Overall accuracy (OA)	0.9484	Overall accuracy (OA) (%)			94.84			
Kappa coefficient (K)	0.9400							

B3: Confusion matrix for 2010

LULC class	Forest	Shrubland	Grassland	cultivated land	Settlement	Row total (RT)	User accuracy (UA) (%)	RT/Total
Forest	88	0	0	0	0	88	100.00	0.1008
Shrubland	0	89	0	10	0	99	89.90	0.1134
Grassland	0	0	277	32	0	309	89.64	0.3540
cultivated land	0	1	11	285	1	298	95.64	0.3414
Settlement	0	0	0	5	74	79	93.67	0.0905
Column total (CT)	88	90	288	332	75	873		
Producer accuracy (PA) (%)	100.00	98.89	96.18	85.84	98.67			
CT/Total	0.1008	0.1031	0.3299	0.3803	0.0859			
Sum of (CT/Total)*(RT/Total)	0.2762							
Overall accuracy (OA)	0.9313	Overall accuracy (OA) (%)			93.13			
Kappa coefficient (K)	0.9050							

B4: Confusion matrix for 2019

LULC class	Forest	Shrubland	Grassland	cultivated land	Settlement	Row total (RT)	User accuracy (UA) (%)	RT/Total
Forest	119	15	0	0	0	134	88.81	0.1524
Shrubland	4	97	0	10	0	111	87.39	0.1263
Grassland	0	1	168	2	0	171	98.25	0.1945
cultivated land	0	2	30	297	3	332	89.46	0.3777
Settlement	0	0	1	10	120	131	91.60	0.1490
Column total (CT)	123	115	199	319	123	879		
Producer accuracy (PA) (%)	96.75	84.35	84.42	93.10	97.56			
CT/Total	0.1399	0.1308	0.2264	0.3629	0.1399			
Sum of (CT/Total)*(RT/Total)	0.2398							
Overall accuracy (OA)	0.9113	Overall accuracy (OA) (%)			91.13			
Kappa coefficient (K)	0.8833							

C1: River cross-section location (lat. and lon.) and reach length from the upstream (C1) to downstream (C17).

River cross-section ID	Longitude (UTM)	Latitude (UTM)	Reach length (m)
C1	351293.9	1309076	0
C2	351378.4	1310329	1373
C3	350674	1310596	2432
C4	351039.9	1311674	2389
C5	349544	1312427	3079
C6	348233.7	1313164	3355
C7	346410.9	1313579	3547
C8	345503.8	1313932	3220
C9	344459.9	1313028	3149
C10	343167.3	1312152	3592
C11	342126.1	1311527	3144
C12	341262.5	1312940	3142
C13	340378.9	1312518	2820
C14	339410.9	1313616	2933
C15	338219.8	1314668	3783
C16	336262.5	1316267	4500

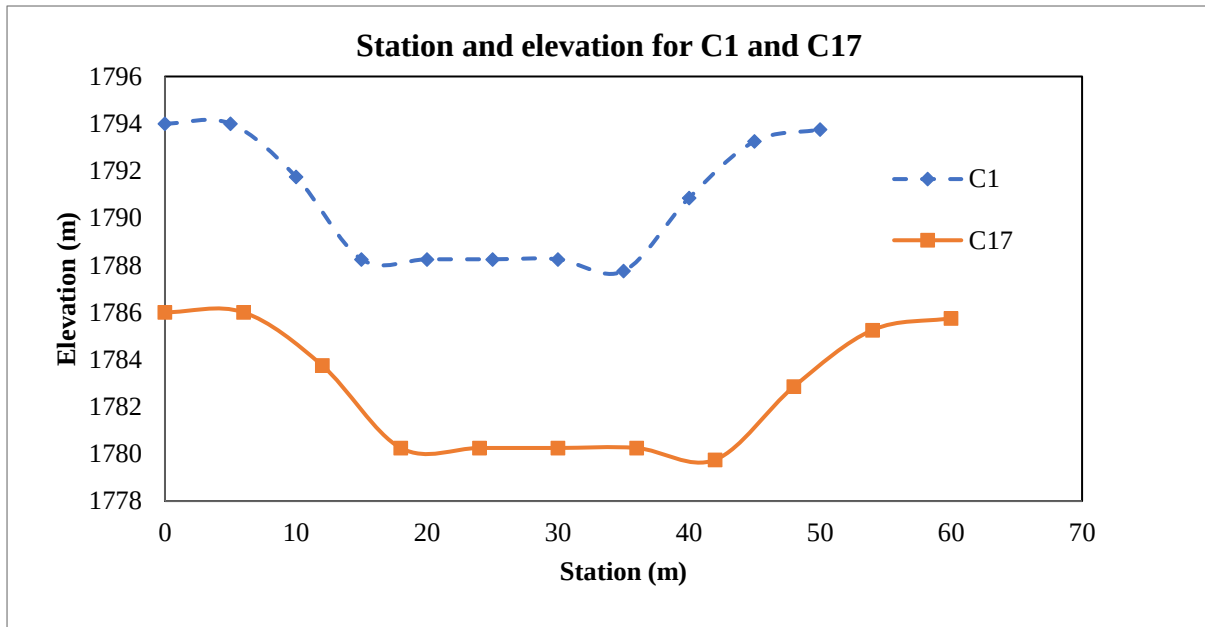
C17	334886.7	1316427	4064
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C2: River cross-section information (station and elevation) used for terrain modification (C1-C17)

	Station (m)	Elevation (m)		Station (m)	Elevation (m)		Station (m)	Elevation (m)
C1	0	1794	C7	0	1792	C13	0	1788
	5	1794		4.6	1792		4.4	1788
	10	1791.75		9.2	1789.75		8.8	1785.75
	15	1788.25		13.8	1786.25		13.2	1782.25
	20	1788.25		18.4	1786.25		17.6	1782.25
	25	1788.25		23	1786.25		22	1782.25
	30	1788.25		27.6	1786.25		26.4	1782.25
	35	1787.75		32.2	1785.75		30.8	1781.75
	40	1790.85		36.8	1788.85		35.2	1784.85
	45	1793.25		41.4	1791.25		39.6	1787.25
C2	50	1793.75	C8	46	1791.75	C14	44	1787.75
	0	1794		0	1792		0	1792
	6	1794		5	1792		4	1792
	12	1791.75		10	1789.75		8	1789.75
	18	1788.25		15	1786.25		12	1786.25
	24	1788.25		20	1786.25		16	1786.25
	30	1788.25		25	1786.25		20	1786.25
	36	1788.25		30	1786.25		24	1786.25
	42	1787.75		35	1785.75		28	1785.75
	48	1790.85		40	1788.85		32	1788.85
C3	54	1793.25	C9	45	1791.25	C15	36	1791.25
	60	1793.75		50	1791.75		40	1791.75
	0	1793		0	1793		0	1789
	5.4	1793		4.6	1793		4.5	1789
	10.8	1790.75		9.2	1790.75		9	1786.75
	16.2	1787.25		13.8	1787.25		13.5	1783.25
	21.6	1787.25		18.4	1787.25		18	1783.25
	27	1787.25		23	1787.25		22.5	1783.25
	32.4	1787.25		27.6	1787.25		27	1783.25
	37.8	1786.75		32.2	1786.75		31.5	1782.75
C4	43.2	1789.85	C10	36.8	1789.85	C16	36	1785.85
	48.6	1792.25		41.4	1792.25		40.5	1788.25
	54	1792.75		46	1792.75		45	1788.75
	0	1792		0	1789		0	1790
	5.8	1792		4.2	1789		4	1790
	11.6	1789.75		8.4	1786.75		8	1787.75
	17.4	1786.25		12.6	1783.25		12	1784.25
	23.2	1786.25		16.8	1783.25		16	1784.25
	29	1786.25		21	1783.25		20	1784.25
	34.8	1786.25		25.2	1783.25		24	1784.25
C5	40.6	1785.75	C11	29.4	1782.75	C17	28	1783.75
	46.4	1788.85		33.6	1785.85		32	1786.85
	52.2	1791.25		37.8	1788.25		36	1789.25
	58	1791.75		42	1788.75		40	1789.75
	0	1794		0	1791		0	1786
	4.5	1794		4.2	1791		6	1786
	9	1791.75		8.4	1788.75		12	1783.75
	13.5	1788.25		12.6	1785.25		18	1780.25
	18	1788.25		16.8	1785.25		24	1780.25
	22.5	1788.25		21	1785.25		30	1780.25
C6	27	1788.25	C12	25.2	1785.25		36	1780.25
	31.5	1787.75		29.4	1784.75		42	1779.75
	36	1790.85		33.6	1787.85		48	1782.85
	40.5	1793.25		37.8	1790.25		54	1785.25
	45	1793.75		42	1790.75		60	1785.75
	0	1792		0	1789			
	4.2	1792		4.2	1789			
	8.4	1789.75		8.4	1786.75			
	12.6	1786.25		12.6	1783.25			
	16.8	1786.25		16.8	1783.25			
	21	1786.25		21	1783.25			
	25.2	1786.25		25.2	1783.25			
	29.4	1785.75		29.4	1782.75			
	33.6	1788.85		33.6	1785.85			

	37.8	1791.25		37.8	1788.25
	42	1791.75		42	1788.75

C3: Rough comparison of station and elevation information for the upstream (C1) and downstream (C17) cross-sections used in terrain modification



C4: Time-series rainfall and streamflow data for the Gumara watershed From July to August, 2019.

